

Survival Analysis Versus Classification

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Contents

1	Introduction	1
2	Preliminaries	2
2.1	Set Working Directory	2
2.2	Load libraries	2
2.3	Load data	4
3	Exploratory data analysis	5
3.1	Look at the data set	5
3.2	Preprocessing of NA value	9
3.3	Replace the NA value with the median value of variable(numeric)	9
3.4	Normalize the data	10
3.5	Recode the target variable	10
3.6	Delete the NA value in the outcome variable	10
3.7	Delete the row that contain NA	10
3.8	Train test split With stratification	10
3.9	Transformation. Transform Label as Factor (Categorical) and Change Column Names (TRAIN- ING data set)	11
4	Machine Learning Classifiers	11
4.1	Classification. Predictive Model. Random Forest Algorithm	11
4.2	Classification. k-Nearest Neighbors (kNN) Algorithm	14
4.3	Classification. Predictive Model. Naive Bayes Algorithm	18
4.4	Classification. Predictive Model. Logistic Regression Algorithm	21
5	Survival Analysis	24
5.1	Preprocessing	24
5.2	Cox Model	24
5.3	Survival Random Forests	27
5.4	Cox Boost Model	28
5.5	Cox Robust Model	29
6	Model comparison and Conclusion	31
6.1	Model Comparison	31
6.2	Conclusion	31

1 Introduction

The wpbc dataset (available at https://archive.ics.uci.edu/ml/machine_learningdatabases/breast-cancer-wisconsin/wpbc.data). It is available at <https://archive.ics.uci.edu/ml/machinelearningdatabases/breast-cancer-wisconsin/wpbc.names>. We want to predict the probability of relapse (“recurrent”) at 24 months. To do this, you will compare the methods of survival analysis (Cox models, survival random forests,...) with

the classification methods. Performance measurements (including AUC) will be made on a test sub-sample consisting of 20 to 30% of the data (be careful to stratify well!).

2 Preliminaries

2.1 Set Working Directory

```
WORKING_DIR <- "C:/Users/HP/Desktop/Lab 4"  
(WORKING_DIR)
```

```
## [1] "C:/Users/HP/Desktop/Lab 4"
```

```
getwd()
```

```
## [1] "C:/Users/HP/Desktop/Lab 4"
```

2.2 Load libraries

```
# Load Libraries
```

```
library(ggfortify)
```

```
## Loading required package: ggplot2
```

```
library(MASS)
```

```
library(knitr) # Markdown
```

```
library(kableExtra)
```

```
library(KMsurv)
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
library(e1071)
```

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-18
```

```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse
```

```
## v tibble 2.1.3      v purrr 0.3.3
```

```
## v tidyr  1.0.0      v dplyr 0.8.3
```

```
## v readr  1.3.1      v stringr 1.4.0
```

```
## v tibble 2.1.3      v forcats 0.4.0
```

```
## -- Conflicts ----- tidyverse_confli
```

```
## x purrr::accumulate() masks foreach::accumulate()
```

```
## x tidyr::expand()     masks Matrix::expand()
```

```
## x dplyr::filter()     masks stats::filter()
```

```
## x dplyr::group_rows() masks kableExtra::group_rows()
```

```
## x dplyr::lag()        masks stats::lag()
```

```
## x purrr::lift()       masks caret::lift()
```

```
## x tidyr::pack()       masks Matrix::pack()
```

```
## x dplyr::select()     masks MASS::select()
```

```
## x tidyr::unpack()     masks Matrix::unpack()
```

```
## x purrr::when()       masks foreach::when()
```

```

library(randomForest)
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:dplyr':
##
##      combine
## The following object is masked from 'package:ggplot2':
##
##      margin
library(randomForestSRC)
##
## randomForestSRC 2.9.1
##
## Type rfsrc.news() to see new features, changes, and bug fixes.
##
## Attaching package: 'randomForestSRC'
## The following object is masked from 'package:purrr':
##
##      partial
## The following objects are masked from 'package:e1071':
##
##      impute, tune
library(survival)
##
## Attaching package: 'survival'
## The following object is masked from 'package:caret':
##
##      cluster
library(foreign) # For reading and writing data stored
library(RWeka) # Weka
##
## Attaching package: 'RWeka'
## The following objects are masked from 'package:foreign':
##
##      read.arff, write.arff
library(ROCR)
## Loading required package: gplots
##
## Attaching package: 'gplots'
## The following object is masked from 'package:stats':
##

```

```

##      lowess
library(pROC)
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
## The following object is masked from 'package:glmnet':
##
##      auc
## The following objects are masked from 'package:stats':
##
##      cov, smooth, var
library(cvAUC) # AUC for classification
## Loading required package: data.table
##
## Attaching package: 'data.table'
## The following objects are masked from 'package:dplyr':
##
##      between, first, last
## The following object is masked from 'package:purrr':
##
##      transpose
##
## cvAUC version: 1.1.0
## Notice to cvAUC users: Major speed improvements in version 1.1.0
##
library(survAUC) # AUC for Survival
library(risksetROC) # AUC for Survival Random Forest
library(CoxBoost) # For Cox Boost Model
## Loading required package: prodlim
library(coxrobust) # For Cox Robust Model

```

2.3 Load data

```

### Load data
wpbc = read_delim("wpbc.data",delim=","col_names=F,na = '?')
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   X2 = col_character()
## )
## See spec(...) for full column specifications.
names_cov = paste0(rep(c('radius','texture','perimeter','area','smoothness','compactness',
                        'concavity','concave_points','symmetry','fractal_dimension'),3),
                  c(rep('_mean',10),rep('_SD',10),rep('_worst',10)))

```

```

names(wdbc) = c('id','recurrent','time',names_cov,c('Tumor_size','Lymph_node_status'))

wdbc = wdbc %>% mutate(id = factor(id)) %>%
  mutate( recurrent = recode_factor(recurrent , "N" = FALSE, 'R' = TRUE ))
glimpse(wdbc)

## Observations: 198
## Variables: 35
## $ id <fct> 119513, 8423, 842517, 843483, 843584, ...
## $ recurrent <fct> FALSE, FALSE, FALSE, FALSE, TRUE, TRUE...
## $ time <dbl> 31, 61, 116, 123, 27, 77, 60, 77, 119,...
## $ radius_mean <dbl> 18.02, 17.99, 21.37, 11.42, 20.29, 12....
## $ texture_mean <dbl> 27.60, 10.38, 17.44, 20.38, 14.34, 15....
## $ perimeter_mean <dbl> 117.50, 122.80, 137.50, 77.58, 135.10,...
## $ area_mean <dbl> 1013.0, 1001.0, 1373.0, 386.1, 1297.0,...
## $ smoothness_mean <dbl> 0.09489, 0.11840, 0.08836, 0.14250, 0....
## $ compactness_mean <dbl> 0.10360, 0.27760, 0.11890, 0.28390, 0....
## $ concavity_mean <dbl> 0.10860, 0.30010, 0.12550, 0.24140, 0....
## $ concave_points_mean <dbl> 0.07055, 0.14710, 0.08180, 0.10520, 0....
## $ symmetry_mean <dbl> 0.1865, 0.2419, 0.2333, 0.2597, 0.1809...
## $ fractal_dimension_mean <dbl> 0.06333, 0.07871, 0.06010, 0.09744, 0....
## $ radius_SD <dbl> 0.6249, 1.0950, 0.5854, 0.4956, 0.7572...
## $ texture_SD <dbl> 1.8900, 0.9053, 0.6105, 1.1560, 0.7813...
## $ perimeter_SD <dbl> 3.972, 8.589, 3.928, 3.445, 5.438, 2.9...
## $ area_SD <dbl> 71.55, 153.40, 82.15, 27.23, 94.44, 30...
## $ smoothness_SD <dbl> 0.004433, 0.006399, 0.006167, 0.009110...
## $ compactness_SD <dbl> 0.014210, 0.049040, 0.034490, 0.074580...
## $ concavity_SD <dbl> 0.03233, 0.05373, 0.03300, 0.05661, 0....
## $ concave_points_SD <dbl> 0.009854, 0.015870, 0.018050, 0.018670...
## $ symmetry_SD <dbl> 0.01694, 0.03003, 0.03094, 0.05963, 0....
## $ fractal_dimension_SD <dbl> 0.003495, 0.006193, 0.005039, 0.009208...
## $ radius_worst <dbl> 21.63, 25.38, 24.90, 14.91, 22.54, 15....
## $ texture_worst <dbl> 37.08, 17.33, 20.98, 26.50, 16.67, 20....
## $ perimeter_worst <dbl> 139.70, 184.60, 159.10, 98.87, 152.20,...
## $ area_worst <dbl> 1436.0, 2019.0, 1949.0, 567.7, 1575.0,...
## $ smoothness_worst <dbl> 0.1195, 0.1622, 0.1188, 0.2098, 0.1374...
## $ compactness_worst <dbl> 0.1926, 0.6656, 0.3449, 0.8663, 0.2050...
## $ concavity_worst <dbl> 0.3140, 0.7119, 0.3414, 0.6869, 0.4000...
## $ concave_points_worst <dbl> 0.11700, 0.26540, 0.20320, 0.25750, 0....
## $ symmetry_worst <dbl> 0.2677, 0.4601, 0.4334, 0.6638, 0.2364...
## $ fractal_dimension_worst <dbl> 0.08113, 0.11890, 0.09067, 0.17300, 0....
## $ Tumor_size <dbl> 5.0, 3.0, 2.5, 2.0, 3.5, 2.5, 1.5, 4.0...
## $ Lymph_node_status <dbl> 5, 2, 0, 0, 0, 0, NA, 10, 1, 20, 0, 0,...

```

3 Exploratory data analysis

```
DATASET <- as.data.frame(wdbc)
```

3.1 Look at the data set

```
head(DATASET)
```

##	id	recurrent	time	radius_mean	texture_mean	perimeter_mean	area_mean
## 1	119513	FALSE	31	18.02	27.60	117.50	1013.0
## 2	8423	FALSE	61	17.99	10.38	122.80	1001.0
## 3	842517	FALSE	116	21.37	17.44	137.50	1373.0
## 4	843483	FALSE	123	11.42	20.38	77.58	386.1
## 5	843584	TRUE	27	20.29	14.34	135.10	1297.0
## 6	843786	TRUE	77	12.75	15.29	84.60	502.7
##	smoothness_mean	compactness_mean	concavity_mean	concave_points_mean			
## 1	0.09489	0.1036	0.1086	0.07055			
## 2	0.11840	0.2776	0.3001	0.14710			
## 3	0.08836	0.1189	0.1255	0.08180			
## 4	0.14250	0.2839	0.2414	0.10520			
## 5	0.10030	0.1328	0.1980	0.10430			
## 6	0.11890	0.1569	0.1664	0.07666			
##	symmetry_mean	fractal_dimension_mean	radius_SD	texture_SD	perimeter_SD		
## 1	0.1865	0.06333	0.6249	1.8900	3.972		
## 2	0.2419	0.07871	1.0950	0.9053	8.589		
## 3	0.2333	0.06010	0.5854	0.6105	3.928		
## 4	0.2597	0.09744	0.4956	1.1560	3.445		
## 5	0.1809	0.05883	0.7572	0.7813	5.438		
## 6	0.1995	0.07164	0.3877	0.7402	2.999		
##	area_SD	smoothness_SD	compactness_SD	concavity_SD	concave_points_SD		
## 1	71.55	0.004433	0.01421	0.03233	0.009854		
## 2	153.40	0.006399	0.04904	0.05373	0.015870		
## 3	82.15	0.006167	0.03449	0.03300	0.018050		
## 4	27.23	0.009110	0.07458	0.05661	0.018670		
## 5	94.44	0.011490	0.02461	0.05688	0.018850		
## 6	30.85	0.007775	0.02987	0.04561	0.013570		
##	symmetry_SD	fractal_dimension_SD	radius_worst	texture_worst			
## 1	0.01694	0.003495	21.63	37.08			
## 2	0.03003	0.006193	25.38	17.33			
## 3	0.03094	0.005039	24.90	20.98			
## 4	0.05963	0.009208	14.91	26.50			
## 5	0.01756	0.005115	22.54	16.67			
## 6	0.01774	0.005114	15.51	20.37			
##	perimeter_worst	area_worst	smoothness_worst	compactness_worst			
## 1	139.70	1436.0	0.1195	0.1926			
## 2	184.60	2019.0	0.1622	0.6656			
## 3	159.10	1949.0	0.1188	0.3449			
## 4	98.87	567.7	0.2098	0.8663			
## 5	152.20	1575.0	0.1374	0.2050			
## 6	107.30	733.2	0.1706	0.4196			
##	concavity_worst	concave_points_worst	symmetry_worst				
## 1	0.3140	0.1170	0.2677				
## 2	0.7119	0.2654	0.4601				
## 3	0.3414	0.2032	0.4334				
## 4	0.6869	0.2575	0.6638				
## 5	0.4000	0.1625	0.2364				
## 6	0.5999	0.1709	0.3485				
##	fractal_dimension_worst	Tumor_size	Lymph_node_status				
## 1	0.08113	5.0	5				
## 2	0.11890	3.0	2				
## 3	0.09067	2.5	0				
## 4	0.17300	2.0	0				

```
## 5          0.07678          3.5          0
## 6          0.11790          2.5          0
```

```
dim(DATASET)
```

```
## [1] 198 35
```

```
colnames(DATASET)
```

```
## [1] "id"          "recurrent"
## [3] "time"        "radius_mean"
## [5] "texture_mean" "perimeter_mean"
## [7] "area_mean"    "smoothness_mean"
## [9] "compactness_mean" "concavity_mean"
## [11] "concave_points_mean" "symmetry_mean"
## [13] "fractal_dimension_mean" "radius_SD"
## [15] "texture_SD"    "perimeter_SD"
## [17] "area_SD"       "smoothness_SD"
## [19] "compactness_SD" "concavity_SD"
## [21] "concave_points_SD" "symmetry_SD"
## [23] "fractal_dimension_SD" "radius_worst"
## [25] "texture_worst"    "perimeter_worst"
## [27] "area_worst"       "smoothness_worst"
## [29] "compactness_worst" "concavity_worst"
## [31] "concave_points_worst" "symmetry_worst"
## [33] "fractal_dimension_worst" "Tumor_size"
## [35] "Lymph_node_status"
```

```
summary(DATASET)
```

```
##      id      recurrent      time      radius_mean
## 8423 : 1 FALSE:151 Min. : 1.00 Min. :10.95
## 85715 : 1 TRUE : 47 1st Qu.: 14.00 1st Qu.:15.05
## 86208 : 1      Median : 39.50 Median :17.29
## 86517 : 1      Mean : 46.73 Mean :17.41
## 87112 : 1      3rd Qu.: 72.75 3rd Qu.:19.58
## 87163 : 1      Max. :125.00 Max. :27.22
## (Other):192
## texture_mean perimeter_mean area_mean smoothness_mean
## Min. :10.38 Min. : 71.90 Min. : 361.6 Min. :0.07497
## 1st Qu.:19.41 1st Qu.: 98.16 1st Qu.: 702.5 1st Qu.:0.09390
## Median :21.75 Median :113.70 Median : 929.1 Median :0.10190
## Mean :22.28 Mean :114.86 Mean : 970.0 Mean :0.10268
## 3rd Qu.:24.66 3rd Qu.:129.65 3rd Qu.:1193.5 3rd Qu.:0.11098
## Max. :39.28 Max. :182.10 Max. :2250.0 Max. :0.14470
##
## compactness_mean concavity_mean concave_points_mean symmetry_mean
## Min. :0.04605 Min. :0.02398 Min. :0.02031 Min. :0.1308
## 1st Qu.:0.11020 1st Qu.:0.10685 1st Qu.:0.06367 1st Qu.:0.1741
## Median :0.13175 Median :0.15135 Median :0.08607 Median :0.1893
## Mean :0.14265 Mean :0.15624 Mean :0.08678 Mean :0.1928
## 3rd Qu.:0.17220 3rd Qu.:0.20050 3rd Qu.:0.10393 3rd Qu.:0.2093
## Max. :0.31140 Max. :0.42680 Max. :0.20120 Max. :0.3040
##
## fractal_dimension_mean radius_SD texture_SD perimeter_SD
## Min. :0.05025 Min. :0.1938 Min. :0.3621 Min. : 1.153
## 1st Qu.:0.05672 1st Qu.:0.3882 1st Qu.:0.9213 1st Qu.: 2.743
```

```

## Median :0.06171      Median :0.5333      Median :1.1685      Median : 3.767
## Mean   :0.06271      Mean   :0.6033      Mean   :1.2645      Mean   : 4.255
## 3rd Qu.:0.06671      3rd Qu.:0.7509      3rd Qu.:1.4632      3rd Qu.: 5.213
## Max.   :0.09744      Max.   :1.8190      Max.   :3.5030      Max.   :13.280
##
##      area_SD      smoothness_SD      compactness_SD      concavity_SD
## Min.   : 13.99      Min.   :0.002667      Min.   :0.007347      Min.   :0.01094
## 1st Qu.: 35.37      1st Qu.:0.005001      1st Qu.:0.019803      1st Qu.:0.02681
## Median : 58.45      Median :0.006193      Median :0.027880      Median :0.03691
## Mean   : 70.23      Mean   :0.006762      Mean   :0.031199      Mean   :0.04075
## 3rd Qu.: 92.48      3rd Qu.:0.007973      3rd Qu.:0.038335      3rd Qu.:0.04897
## Max.   :316.00      Max.   :0.031130      Max.   :0.135400      Max.   :0.14380
##
##      concave_points_SD      symmetry_SD      fractal_dimension_SD
## Min.   :0.005174      Min.   :0.007882      Min.   :0.001087
## 1st Qu.:0.011423      1st Qu.:0.014795      1st Qu.:0.002748
## Median :0.014175      Median :0.017905      Median :0.003719
## Mean   :0.015099      Mean   :0.020555      Mean   :0.003987
## 3rd Qu.:0.017665      3rd Qu.:0.022880      3rd Qu.:0.004630
## Max.   :0.039270      Max.   :0.060410      Max.   :0.012560
##
##      radius_worst      texture_worst      perimeter_worst      area_worst
## Min.   :12.84      Min.   :16.67      Min.   : 85.1      Min.   : 508.1
## 1st Qu.:17.63      1st Qu.:26.21      1st Qu.:118.1      1st Qu.: 947.3
## Median :20.52      Median :30.14      Median :136.5      Median :1295.0
## Mean   :21.02      Mean   :30.14      Mean   :140.3      Mean   :1405.0
## 3rd Qu.:23.73      3rd Qu.:33.55      3rd Qu.:159.9      3rd Qu.:1694.2
## Max.   :35.13      Max.   :49.54      Max.   :232.2      Max.   :3903.0
##
##      smoothness_worst      compactness_worst      concavity_worst
## Min.   :0.08191      Min.   :0.05131      Min.   :0.02398
## 1st Qu.:0.12932      1st Qu.:0.24870      1st Qu.:0.32215
## Median :0.14185      Median :0.35130      Median :0.40235
## Mean   :0.14392      Mean   :0.36510      Mean   :0.43669
## 3rd Qu.:0.15488      3rd Qu.:0.42368      3rd Qu.:0.54105
## Max.   :0.22260      Max.   :1.05800      Max.   :1.17000
##
##      concave_points_worst      symmetry_worst      fractal_dimension_worst
## Min.   :0.02899      Min.   :0.1565      Min.   :0.05504
## 1st Qu.:0.15265      1st Qu.:0.2759      1st Qu.:0.07658
## Median :0.17925      Median :0.3103      Median :0.08689
## Mean   :0.17878      Mean   :0.3234      Mean   :0.09083
## 3rd Qu.:0.20713      3rd Qu.:0.3588      3rd Qu.:0.10138
## Max.   :0.29030      Max.   :0.6638      Max.   :0.20750
##
##      Tumor_size      Lymph_node_status
## Min.   : 0.400      Min.   : 0.000
## 1st Qu.: 1.500      1st Qu.: 0.000
## Median : 2.500      Median : 1.000
## Mean   : 2.847      Mean   : 3.211
## 3rd Qu.: 3.500      3rd Qu.: 4.000
## Max.   :10.000      Max.   :27.000
##
##      NA's      :4

```


3.2 Preprocessing of NA value

```
summary(is.na(DATASET))

##      id      recurrent      time      radius_mean
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198    FALSE:198    FALSE:198    FALSE:198
##
## texture_mean  perimeter_mean  area_mean    smoothness_mean
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198    FALSE:198    FALSE:198    FALSE:198
##
## compactness_mean concavity_mean  concave_points_mean symmetry_mean
## Mode :logical   Mode :logical   Mode :logical      Mode :logical
## FALSE:198      FALSE:198      FALSE:198          FALSE:198
##
## fractal_dimension_mean radius_SD      texture_SD      perimeter_SD
## Mode :logical          Mode :logical Mode :logical   Mode :logical
## FALSE:198              FALSE:198      FALSE:198       FALSE:198
##
## area_SD      smoothness_SD  compactness_SD  concavity_SD
## Mode :logical Mode :logical   Mode :logical   Mode :logical
## FALSE:198    FALSE:198      FALSE:198       FALSE:198
##
## concave_points_SD symmetry_SD      fractal_dimension_SD radius_worst
## Mode :logical      Mode :logical   Mode :logical      Mode :logical
## FALSE:198          FALSE:198      FALSE:198          FALSE:198
##
## texture_worst  perimeter_worst area_worst      smoothness_worst
## Mode :logical  Mode :logical   Mode :logical   Mode :logical
## FALSE:198      FALSE:198      FALSE:198       FALSE:198
##
## compactness_worst concavity_worst concave_points_worst symmetry_worst
## Mode :logical     Mode :logical   Mode :logical      Mode :logical
## FALSE:198         FALSE:198      FALSE:198          FALSE:198
##
## fractal_dimension_worst Tumor_size      Lymph_node_status
## Mode :logical          Mode :logical   Mode :logical
## FALSE:198              FALSE:198      FALSE:194
##                        TRUE :4
```

3.3 Replace the NA value with the median value of variable(numeric)

```
DATASET = DATASET %>% replace_na(list(`Lymph_node_status` = median(DATASET$`Lymph_node_status`, na.rm =
# Verification
summary(is.na(DATASET))

##      id      recurrent      time      radius_mean
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198    FALSE:198    FALSE:198    FALSE:198
##
## texture_mean  perimeter_mean  area_mean    smoothness_mean
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198    FALSE:198    FALSE:198    FALSE:198
##
## compactness_mean concavity_mean  concave_points_mean symmetry_mean
## Mode :logical   Mode :logical   Mode :logical      Mode :logical
## FALSE:198      FALSE:198      FALSE:198          FALSE:198
```

```
## fractal_dimension_mean radius_SD texture_SD perimeter_SD
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198 FALSE:198
## area_SD smoothness_SD compactness_SD concavity_SD
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198 FALSE:198
## concave_points_SD symmetry_SD fractal_dimension_SD radius_worst
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198 FALSE:198
## texture_worst perimeter_worst area_worst smoothness_worst
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198 FALSE:198
## compactness_worst concavity_worst concave_points_worst symmetry_worst
## Mode :logical Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198 FALSE:198
## fractal_dimension_worst Tumor_size Lymph_node_status
## Mode :logical Mode :logical Mode :logical
## FALSE:198 FALSE:198 FALSE:198
```

3.4 Normalize the data

```
# Normalized dataset
normalize <- function(x){
  return ((x-mean(x, na.rm = T))/(sd(x, na.rm = T)))
}
DATASET_NORMALIZE = DATASET %>% mutate_at(-c(1,2,3), normalize)
```

3.5 Recode the target variable

```
DATASET_NORMALIZE = DATASET_NORMALIZE %>% arrange(time)
DATASET_FINAL = DATASET_NORMALIZE %>%
  mutate(outcome_classif =
    ifelse((time <= 24)&(recurrent==TRUE),1,
    ifelse((time > 24)&(recurrent==TRUE),0,
    ifelse((time > 24)&(recurrent==FALSE),0,NA))))
```

3.6 Delete the NA value in the outcome variable

```
DATASET_FINAL = DATASET_FINAL[!is.na(DATASET_FINAL[, "outcome_classif"]),]
```

3.7 Delete the row that contain NA

```
DATASET_FINAL = na.omit(DATASET_FINAL)
```

3.8 Train test split With stratification

```
set.seed(1234)
DATASET_FINAL = DATASET_FINAL %>% mutate(id_1n = c(1:nrow(DATASET_FINAL)))
train_index = createDataPartition(DATASET_FINAL$recurrent, p = 0.8, list = FALSE, times = 1)

DATASET_TRAIN = DATASET_FINAL[train_index,]
DATASET_TEST = DATASET_FINAL[-train_index,]

print(nrow(DATASET_TRAIN))
```

```
## [1] 127
print(nrow(DATASET_TEST))
## [1] 31
```

3.9 Transformation. Transform Label as Factor (Categorical) and Change Column Names (TRAINING data set)

```
DATASET_TRAIN = dplyr::select(DATASET_TRAIN,-c("id","recurrent","time","id_1n"))
DATASET_TEST = dplyr::select(DATASET_TEST,-c("id","recurrent","time","id_1n"))

DATASET_TRAIN$outcome_classif <- as.factor(DATASET_TRAIN$outcome_classif) # As Category
class(DATASET_TRAIN$outcome_classif)
## [1] "factor"
levels(DATASET_TRAIN$outcome_classif)
## [1] "0" "1"
```

4 Machine Learning Classifiers

4.1 Classification. Predictive Model. Random Forest Algorithm

```
pc <- proc.time()
model.forest <- randomForest(DATASET_TRAIN$outcome_classif ~ ., method="class", data = DATASET_TRAIN)
proc.time() - pc

##      user  system elapsed
##    0.09    0.00    0.09
```

4.1.1 Confusion Matrix (Random Forest)

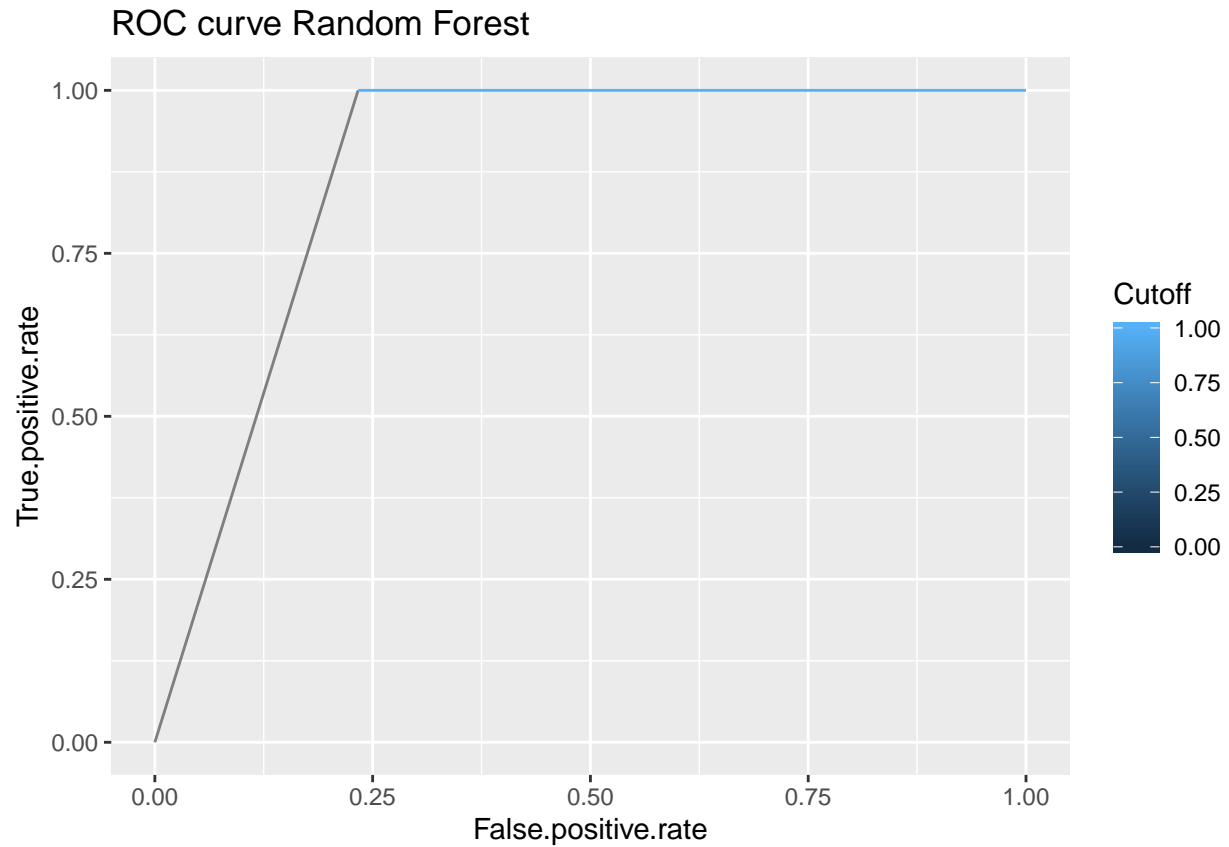
```
prediction.forest <- predict(model.forest, newdata=DATASET_TEST, type='class')
table("Actual Class" = DATASET_TEST$outcome_classif, "Predicted Class"=prediction.forest)

##              Predicted Class
## Actual Class  0  1
##              0 23  0
##              1  7  1

error.rate.forest <- sum(DATASET_TEST$outcome_classif != prediction.forest) / nrow(DATASET_TEST)
accuracy.forest <- 1 - error.rate.forest
print(paste0("Accuary Random Forest (Precision): ", accuracy.forest))
## [1] "Accuary Random Forest (Precision): 0.774193548387097"
```

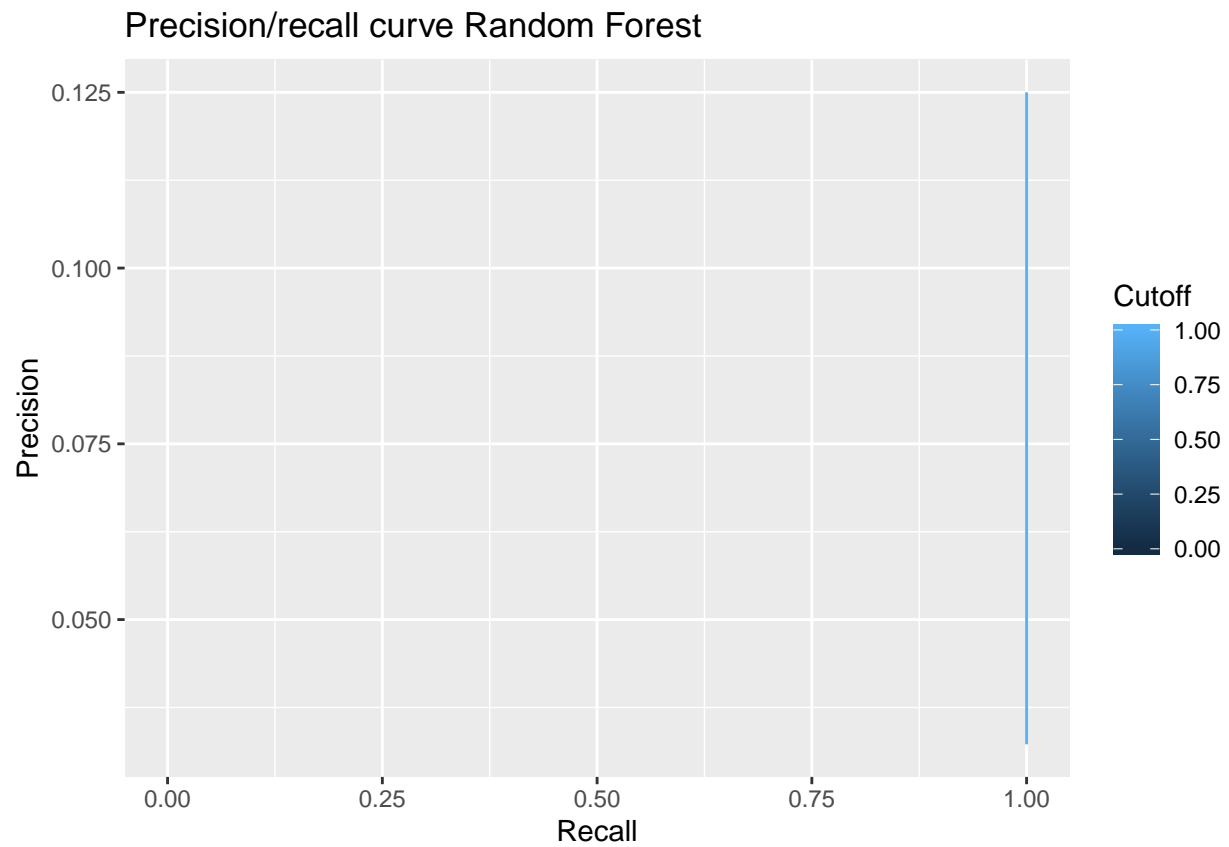
4.1.2 ROC curve Random Forest (x-axis: fpr, y-axis: tpr)

```
pred.forest <- prediction(DATASET_TEST$outcome_classif, prediction.forest)
perf.forest <- performance(pred.forest, "tpr", "fpr")
autoplot(perf.forest, main = 'ROC curve Random Forest')
```



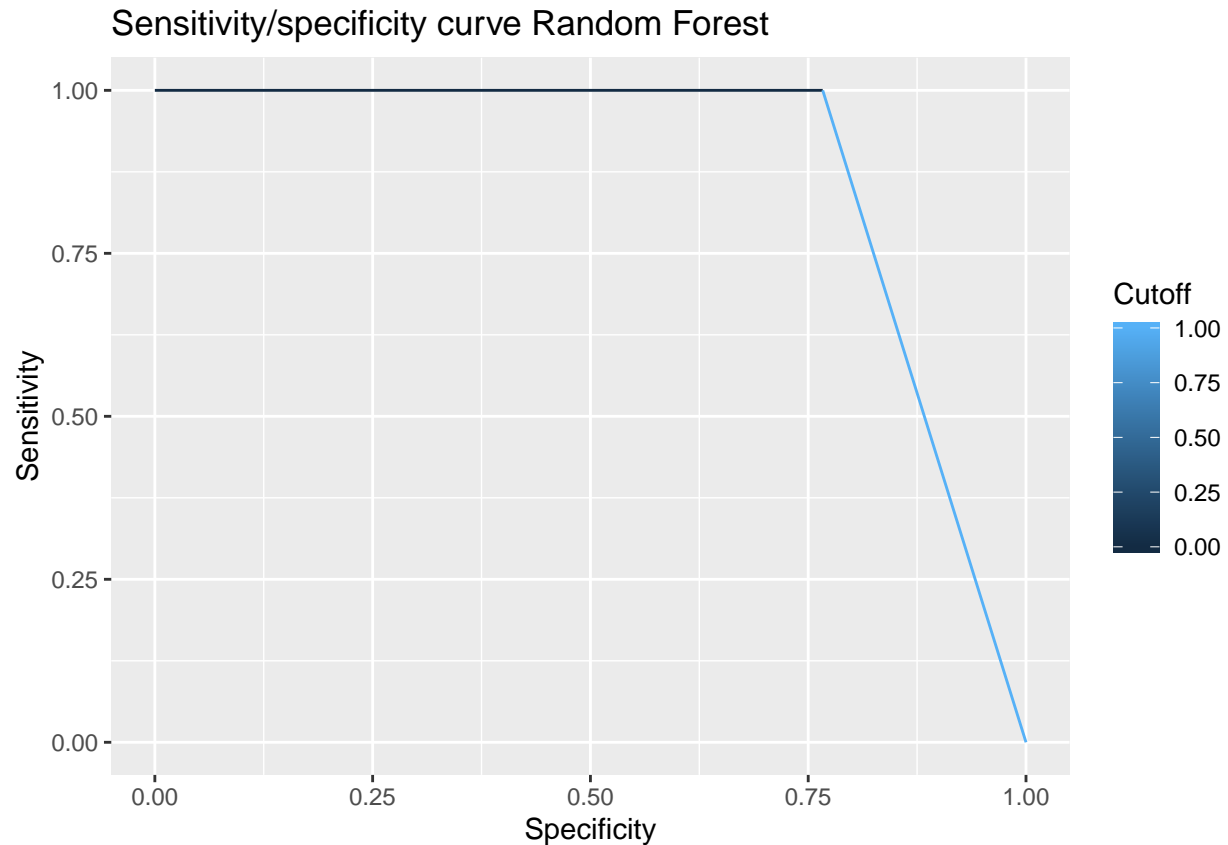
4.1.3 Precision/recall curve Random Forest (x-axis: recall, y-axis: precision)

```
perf2.forest <- performance(pred.forest, "prec", "rec")
autoplot(perf2.forest, main = 'Precision/recall curve Random Forest')
## Warning: Removed 1 rows containing missing values (geom_path).
```



4.1.4 Sensitivity/specificity curve Random Forest (x-axis: specificity, y-axis: sensitivity)

```
perf2.forest <- performance(pred.forest, "sens", "spec")  
autoplot(perf2.forest, main = 'Sensitivity/specificity curve Random Forest')
```



4.1.5 AUC Random Forest

```
auc.forest <- AUC(DATASET_TEST$outcome_classif, prediction.forest)
print (paste0("AUC Random Forest : ", auc.forest))
## [1] "AUC Random Forest : 0.8833333333333333"
```

4.2 Classification. k-Nearest Neighbors (kNN) Algorithm

```
pc <- proc.time()
model.knn <- IBk(DATASET_TRAIN$outcome_classif ~ . , data=DATASET_TRAIN)
proc.time() - pc

##      user  system elapsed
##    0.25    0.02    0.14

summary(model.knn)

##
## === Summary ===
##
## Correctly Classified Instances      127          100    %
## Incorrectly Classified Instances     0             0    %
## Kappa statistic                      1
## Mean absolute error                  0.0078
## Root mean squared error              0.0078
## Relative absolute error              2.7735 %
```

```
## Root relative squared error          2.0865 %
## Total Number of Instances          127
##
## === Confusion Matrix ===
##
##      a   b   <-- classified as
## 106    0 |   a = 0
##    0   21 |   b = 1
```

4.2.1 Confusion Matrix (kNN)

```
prediction.knn <- predict(model.knn, newdata=DATASET_TEST, type='class')
table("Actual Class"=DATASET_TEST$outcome_classif, "Predicted Class"=prediction.knn)

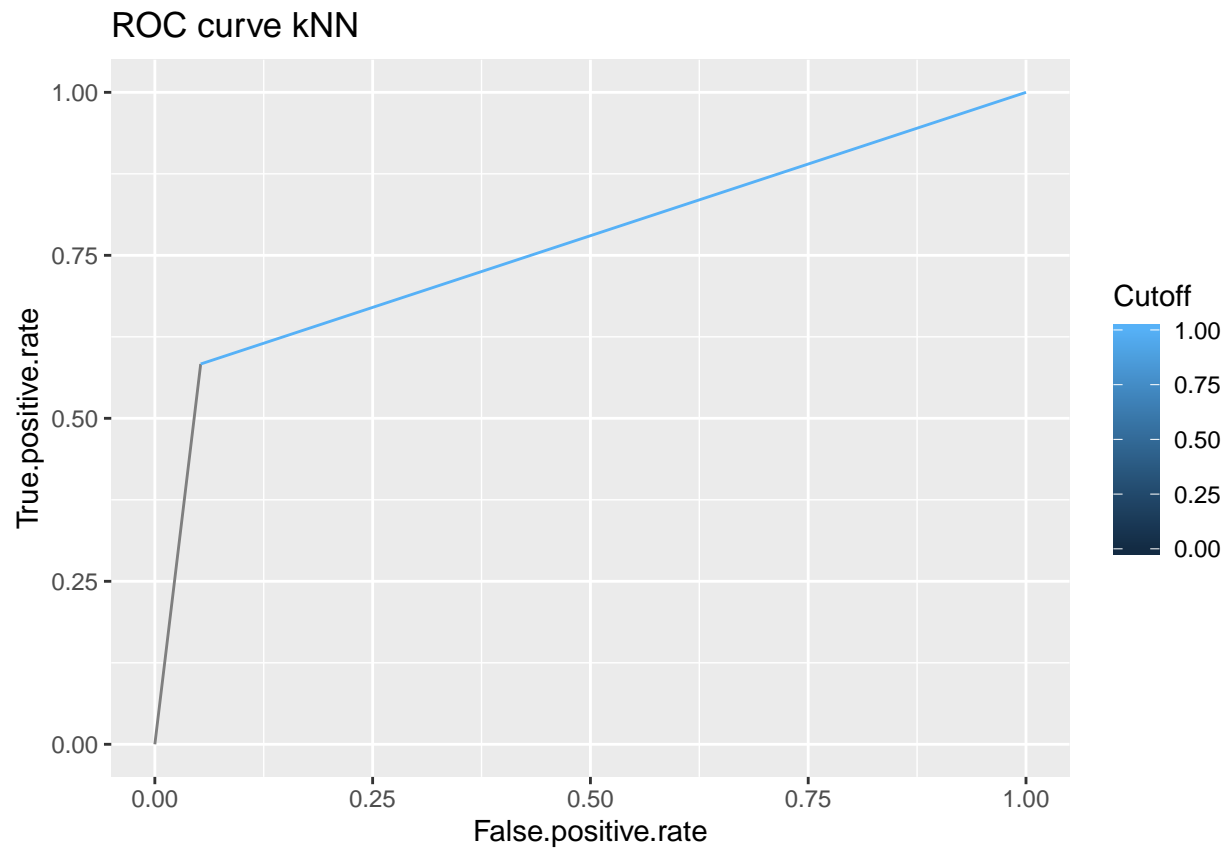
##              Predicted Class
## Actual Class  0  1
##              0 18  5
##              1  1  7

error.rate.knn <- sum(DATASET_TEST$outcome_classif != prediction.knn) / nrow(DATASET_TEST)
print(paste0("Accuary kNN (Precision): ", 1 - error.rate.knn))

## [1] "Accuary kNN (Precision): 0.806451612903226"
```

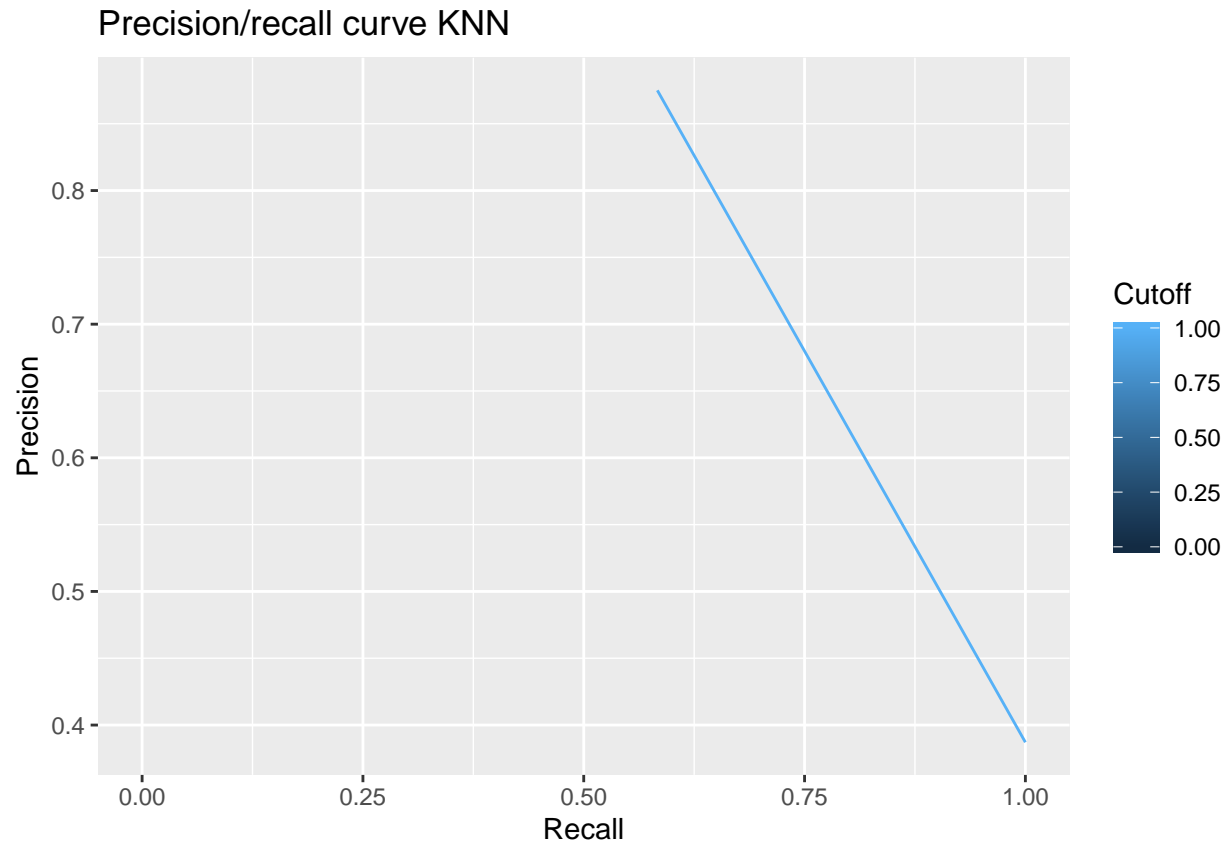
4.2.2 ROC curve kNN (x-axis: fpr, y-axis: tpr)

```
pred.knn <- prediction(DATASET_TEST$outcome_classif, prediction.knn)
perf.knn <- performance(pred.knn, "tpr", "fpr")
autoplot(perf.knn, main = 'ROC curve kNN')
```



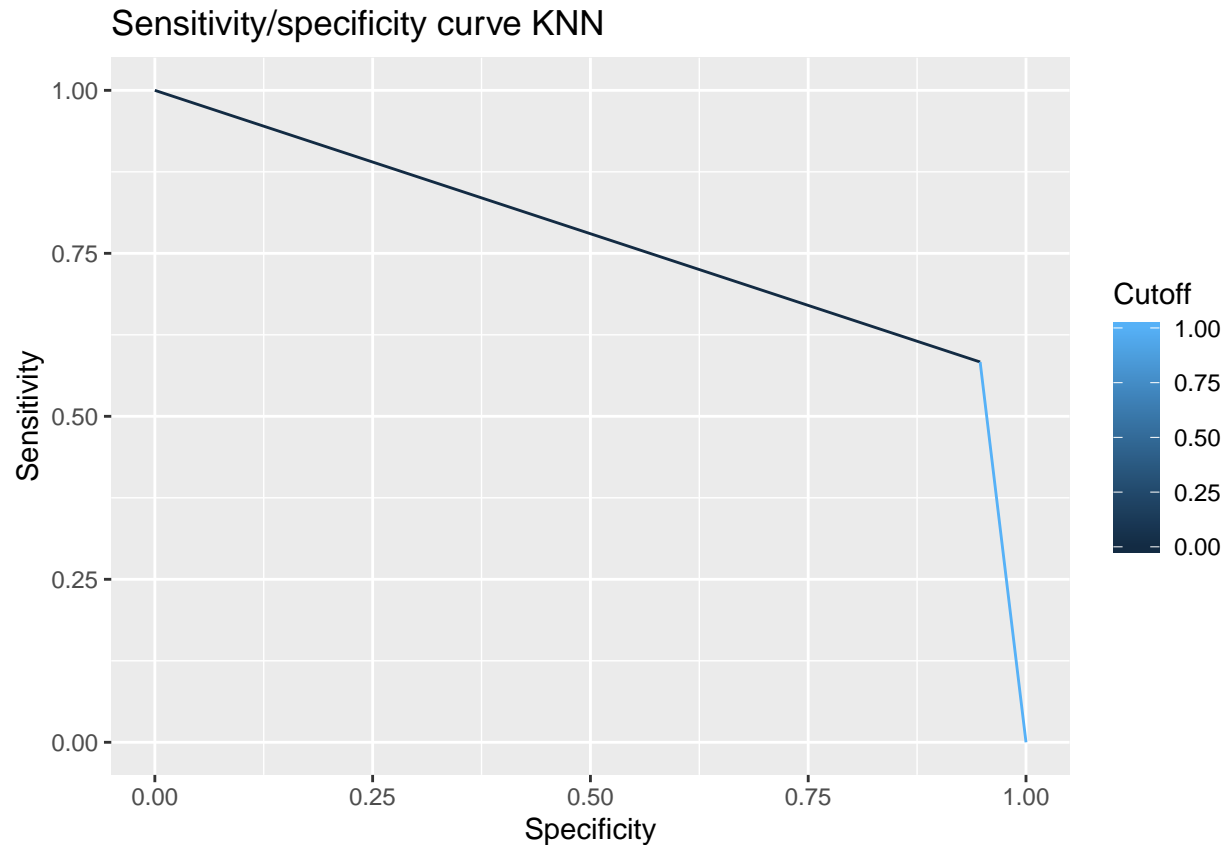
4.2.3 Precision/recall curve KNN (x-axis: recall, y-axis: precision)

```
perf2.knn <- performance(pred.knn, "prec", "rec")
autoplot(perf2.knn, main = 'Precision/recall curve KNN')
## Warning: Removed 1 rows containing missing values (geom_path).
```

4.2.4 Sensitivity/specificity curve KNN (x-axis: specificity, y-axis: sensitivity)

```
perf2.knn <- performance(pred.knn, "sens", "spec")  
autoplot(perf2.knn, main = 'Sensitivity/specificity curve KNN')
```



4.2.5 AUC KNN

```
auc.knn <- AUC(DATASET_TEST$outcome_classif, prediction.knn)
print (paste0("AUC KNN : ", auc.knn))
## [1] "AUC KNN : 0.765350877192983"
```

4.3 Classification. Predictive Model. Naive Bayes Algorithm

```
pc <- proc.time()
model.naiveBayes <- naiveBayes(DATASET_TRAIN$outcome_classif ~ . , data=DATASET_TRAIN)
proc.time() - pc

##      user  system elapsed
##    0.01    0.00    0.01

summary(model.naiveBayes)

##           Length Class  Mode
## apriori      2      table numeric
## tables     32     -none- list
## levels       2     -none- character
## isnumeric   32     -none- logical
## call         4     -none- call
```

4.3.1 Confusion Matrix (naiveBayes)

```
prediction.naiveBayes <- predict(model.naiveBayes, newdata=DATASET_TEST, type='class')
table("Actual Class"=DATASET_TEST$outcome_classif, "Predicted Class"=prediction.naiveBayes)

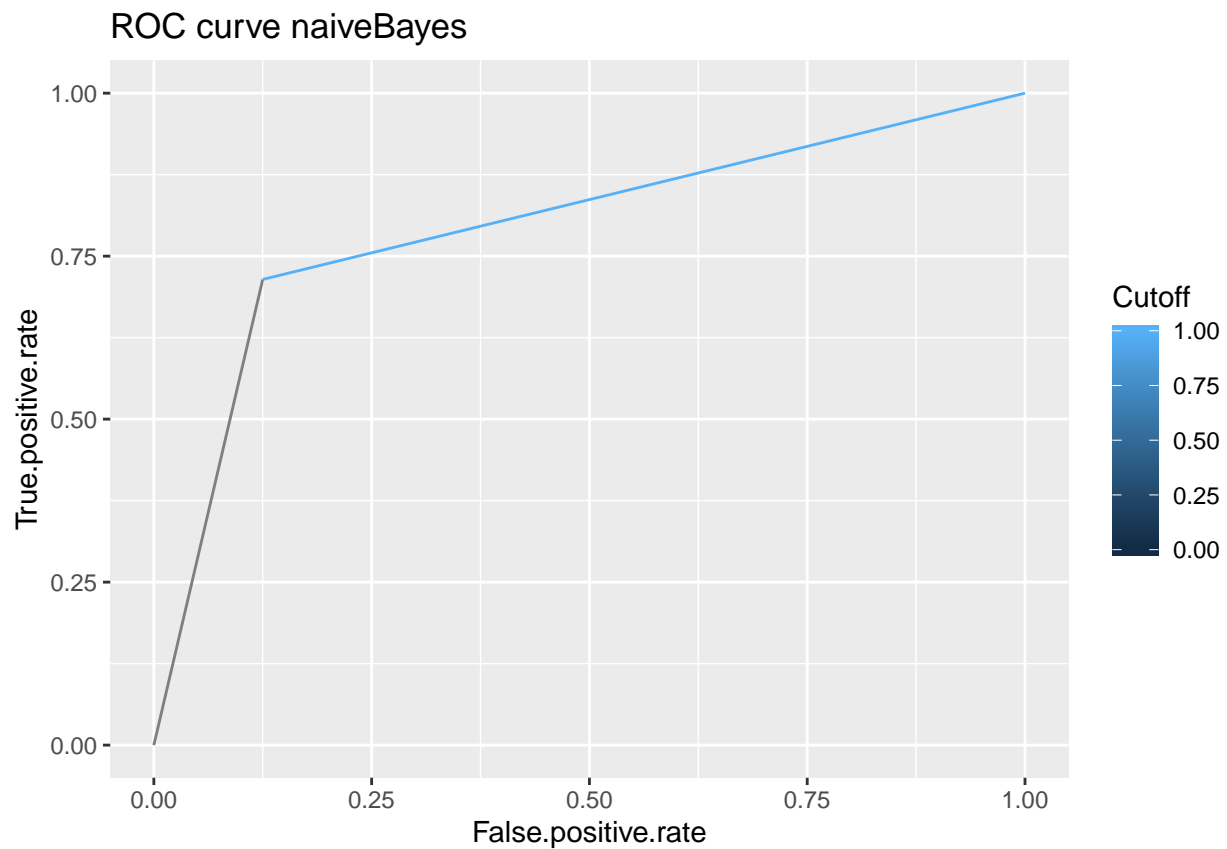
##           Predicted Class
## Actual Class 0  1
##           0 21  2
##           1  3  5

error.rate.naiveBayes <- sum(DATASET_TEST$outcome_classif != prediction.naiveBayes) / nrow(DATASET_TEST)
print(paste0("Accuary naiveBayes (Precision): ", 1 - error.rate.naiveBayes))

## [1] "Accuary naiveBayes (Precision): 0.838709677419355"
```

4.3.2 ROC curve naiveBayes (x-axis: fpr, y-axis: tpr)

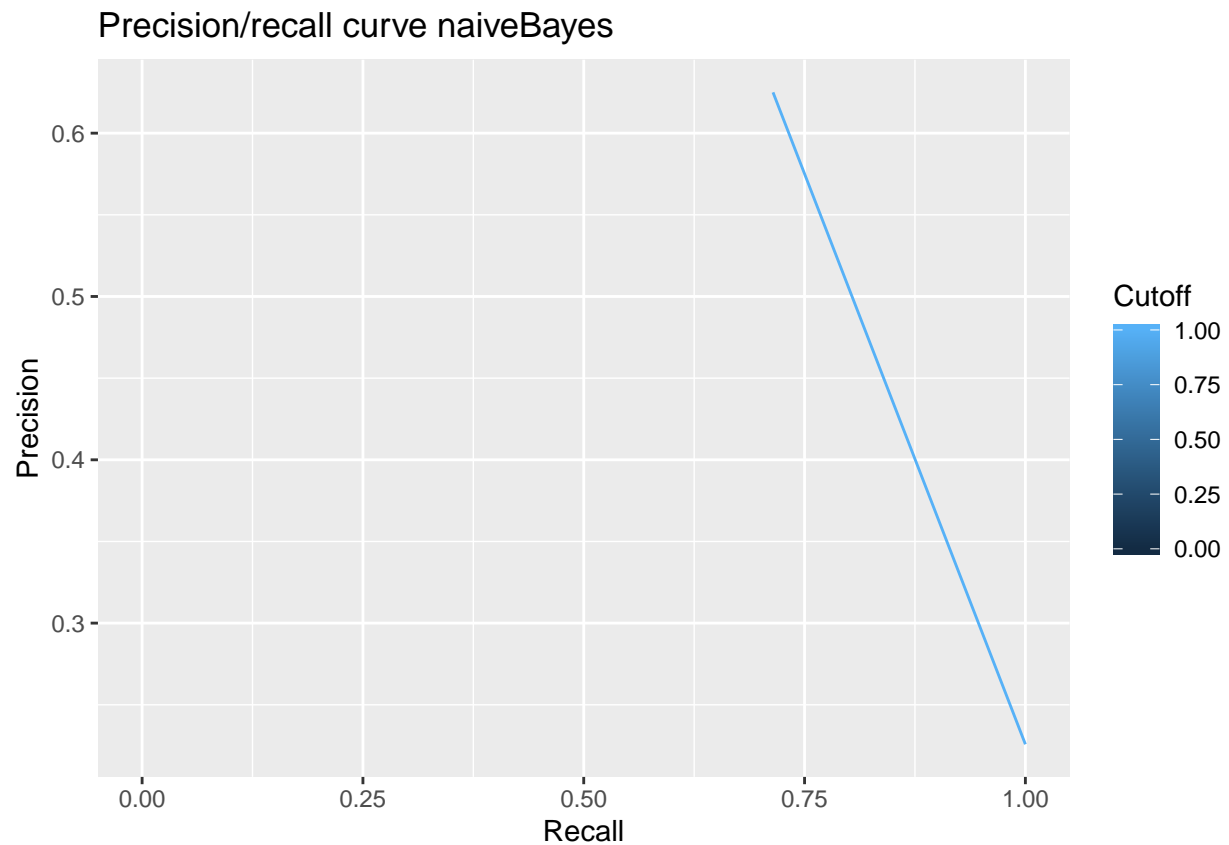
```
pred.naiveBayes <- prediction(DATASET_TEST$outcome_classif, prediction.naiveBayes)
perf.naiveBayes <- performance(pred.naiveBayes, "tpr", "fpr")
autoplot(perf.naiveBayes, main = 'ROC curve naiveBayes')
```



4.3.3 Precision/recall curve naiveBayes (x-axis: recall, y-axis: precision)

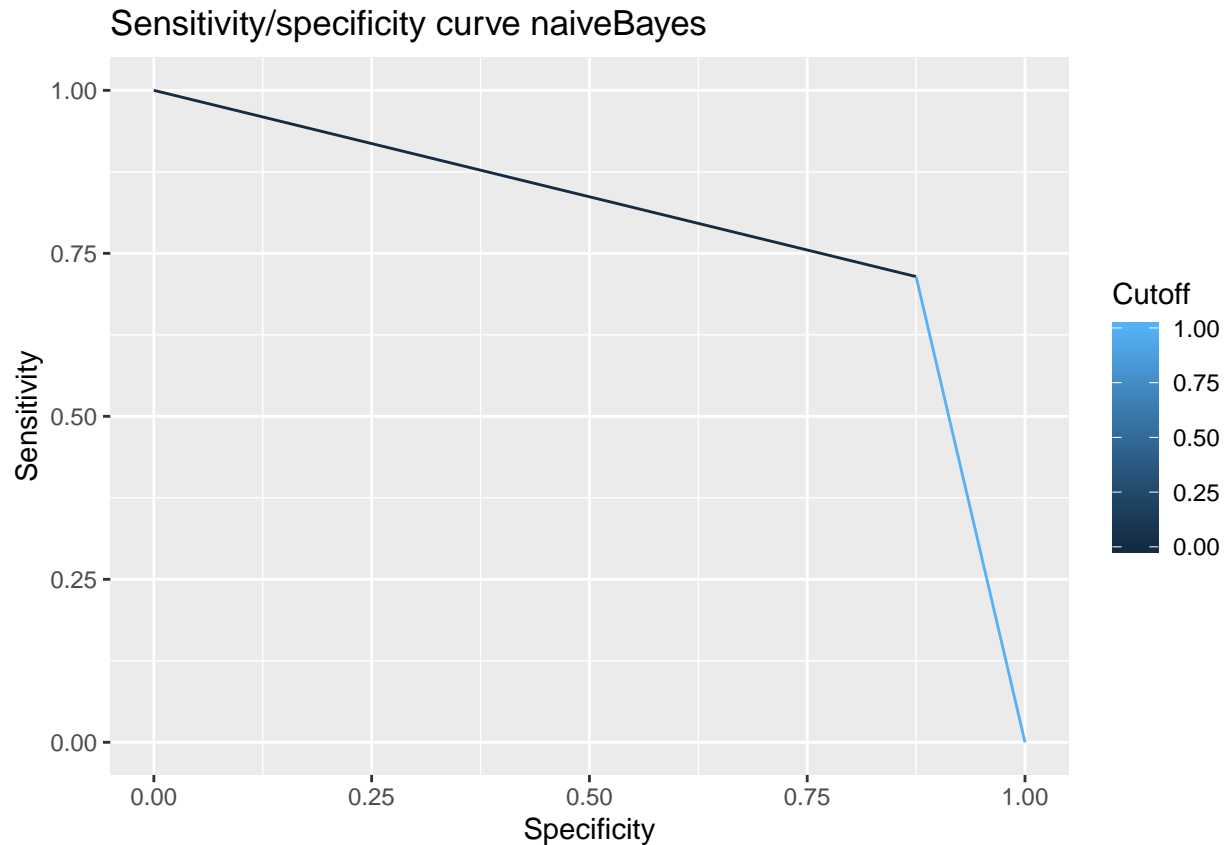
```
perf2.naiveBayes <- performance(pred.naiveBayes, "prec", "rec")
autoplot(perf2.naiveBayes, main = 'Precision/recall curve naiveBayes')

## Warning: Removed 1 rows containing missing values (geom_path).
```



4.3.4 Sensitivity/specificity curve naiveBayes (x-axis: specificity, y-axis: sensitivity)

```
perf2.naiveBayes <- performance(pred.naiveBayes, "sens", "spec")  
autoplot(perf2.naiveBayes, main = 'Sensitivity/specificity curve naiveBayes')
```



4.3.5 AUC naiveBayes

```
auc.naiveBayes <- AUC(DATASET_TEST$outcome_classif, prediction.naiveBayes)
print (paste0("AUC naiveBayes : ", auc.naiveBayes))
## [1] "AUC naiveBayes : 0.794642857142857"
```

4.4 Classification. Predictive Model. Logistic Regression Algorithm

```
pc <- proc.time()
model.logistic <- glm(DATASET_TRAIN$outcome_classif ~ . , data=DATASET_TRAIN, family = binomial(logit))
proc.time() - pc

##      user   system elapsed
##         0         0         0
```

4.4.1 Confusion Matrix (Logistic Regression)

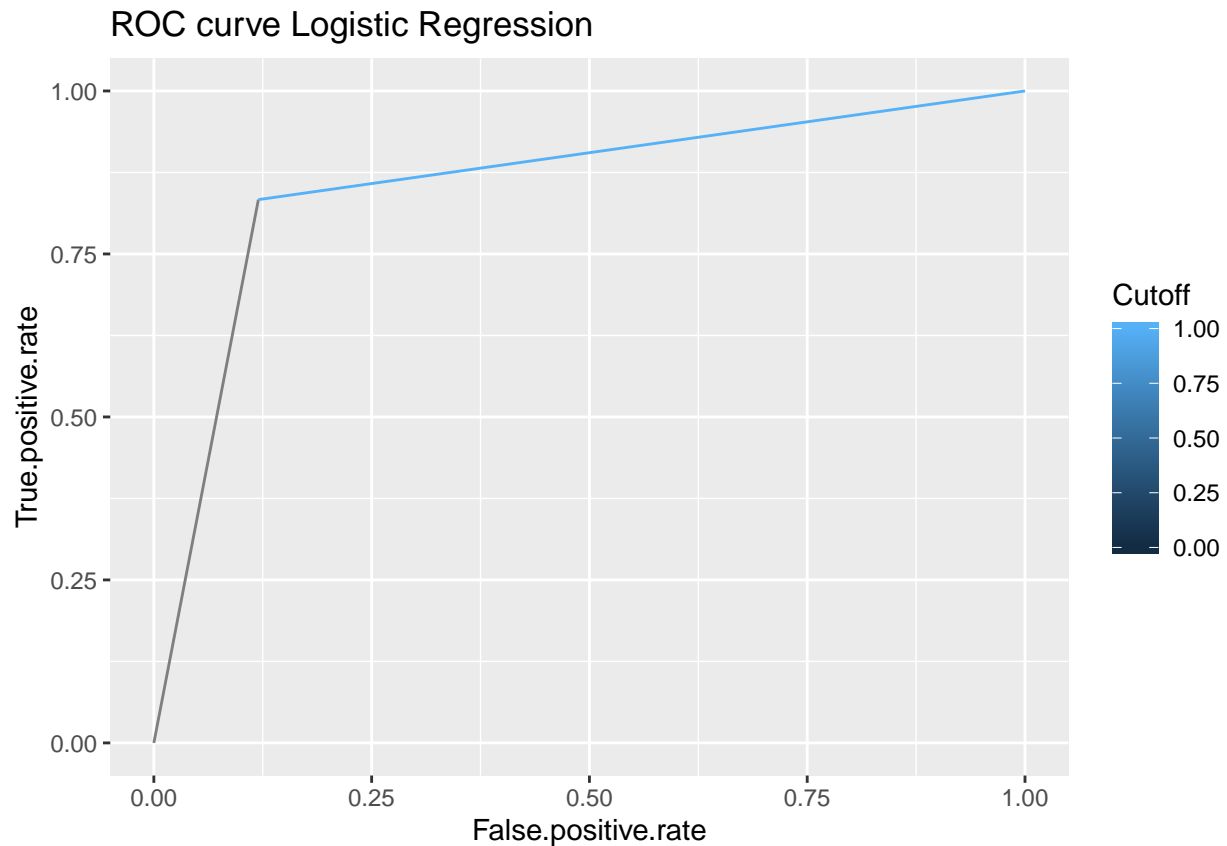
```
prediction.logistic <- predict.glm(model.logistic, newdata=DATASET_TEST, type="response")
sprediction.logistic <- prediction.logistic > 0.5
confusion.matrix <- table("Actual Class" = DATASET_TEST$outcome_classif, "Predicted Class" = sprediction.logistic)
confusion.matrix

##              Predicted Class
## Actual Class FALSE TRUE
##           0     22     1
##           1      3     5
```

```
error.rate.logistic <- (confusion.matrix[2,1]+confusion.matrix[1,2])/sum(confusion.matrix)
print(paste0("Accuracy Logistic Regression (Precision): ", 1 - error.rate.logistic))
## [1] "Accuracy Logistic Regression (Precision): 0.870967741935484"
```

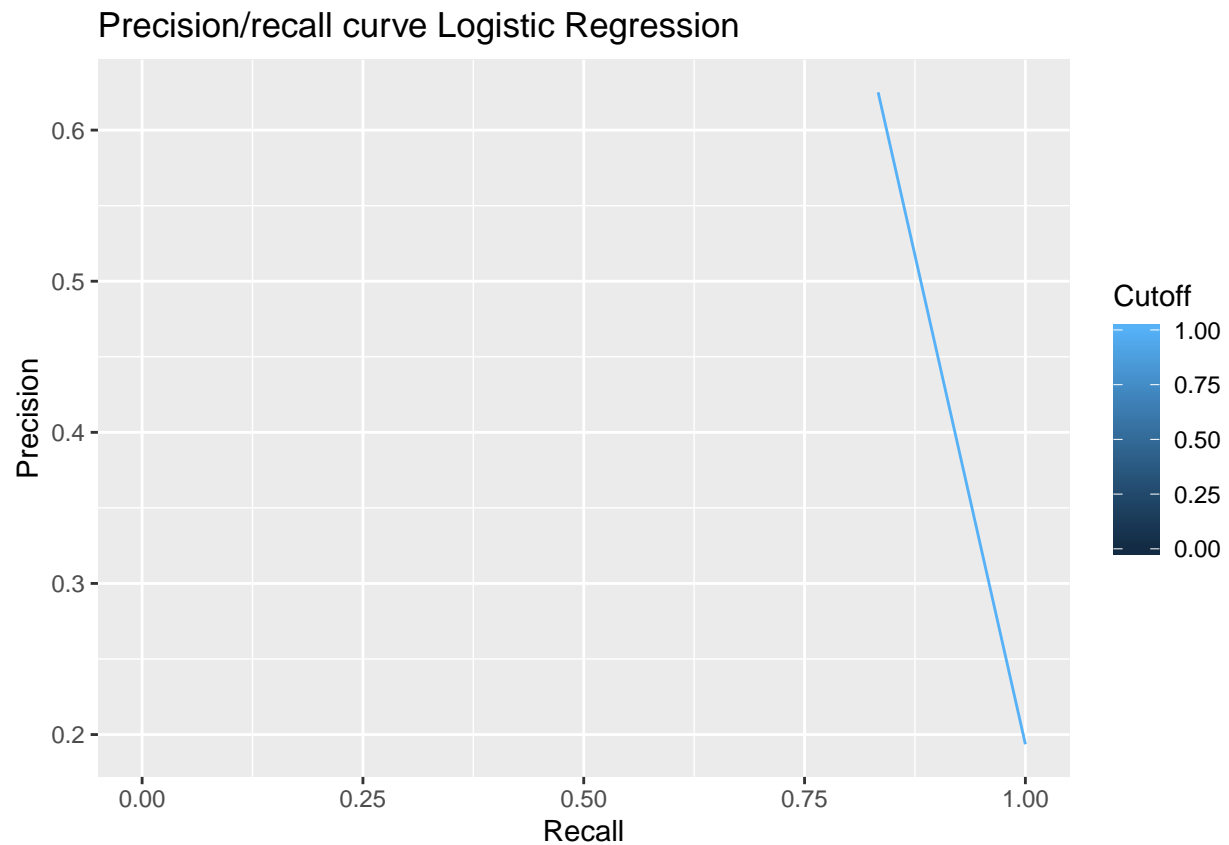
4.4.2 ROC curve Logistic Regression (x-axis: fpr, y-axis: tpr)

```
pred.logistic <- prediction(DATASET_TEST$outcome_classif, sprediction.logistic)
perf.logistic <- performance(pred.logistic, "tpr", "fpr")
autoplot(perf.logistic, main = 'ROC curve Logistic Regression')
```



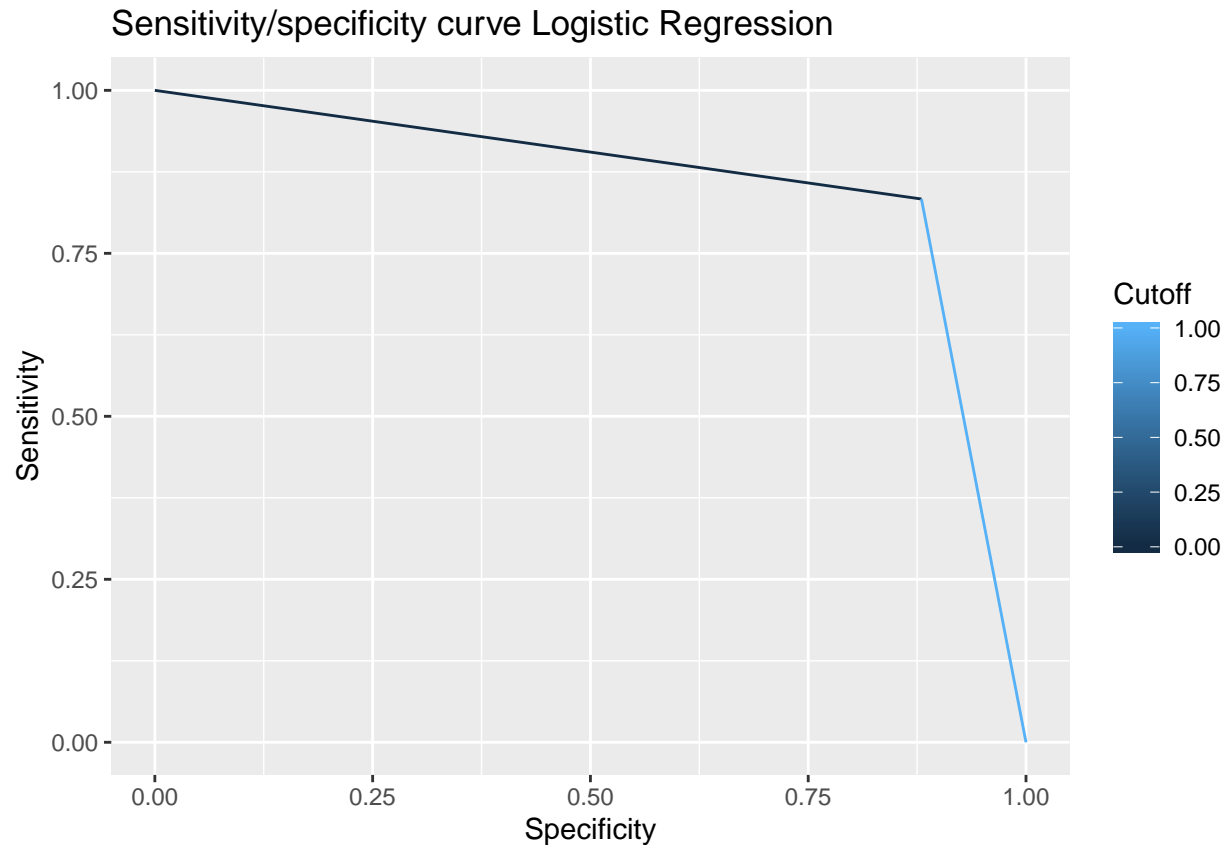
4.4.3 Precision/recall curve Logistic Regression (x-axis: recall, y-axis: precision)

```
perf2.logistic <- performance(pred.logistic, "prec", "rec")
autoplot(perf2.logistic, main = 'Precision/recall curve Logistic Regression')
## Warning: Removed 1 rows containing missing values (geom_path).
```



4.4.4 Sensitivity/specificity curve Logistic Regression (x-axis: specificity, y-axis: sensitivity)

```
perf2.logistic <- performance(pred.logistic, "sens", "spec")  
autoplot(perf2.logistic, main = 'Sensitivity/specificity curve Logistic Regression')
```



4.4.5 AUC Logistic Regression

```
auc.logistic <- AUC(DATASET_TEST$outcome_classif, sprediction.logistic)
print (paste0("AUC : ", auc.logistic))
## [1] "AUC : 0.8566666666666667"
```

5 Survival Analysis

5.1 Preprocessing

```
DATASET_TRAIN2 = DATASET_FINAL[train_index,]
DATASET_TEST2 = DATASET_FINAL[-train_index,]

DATASET_TRAIN3 = dplyr::select(DATASET_TRAIN2,-c("id","id_1n","outcome_classif"))
DATASET_TRAIN3$recurrent = as.logical(DATASET_TRAIN3$recurrent)

DATASET_TEST3 = dplyr::select(DATASET_TEST2,-c("id","id_1n","outcome_classif"))
DATASET_TEST3$recurrent = as.logical(DATASET_TEST3$recurrent)
```

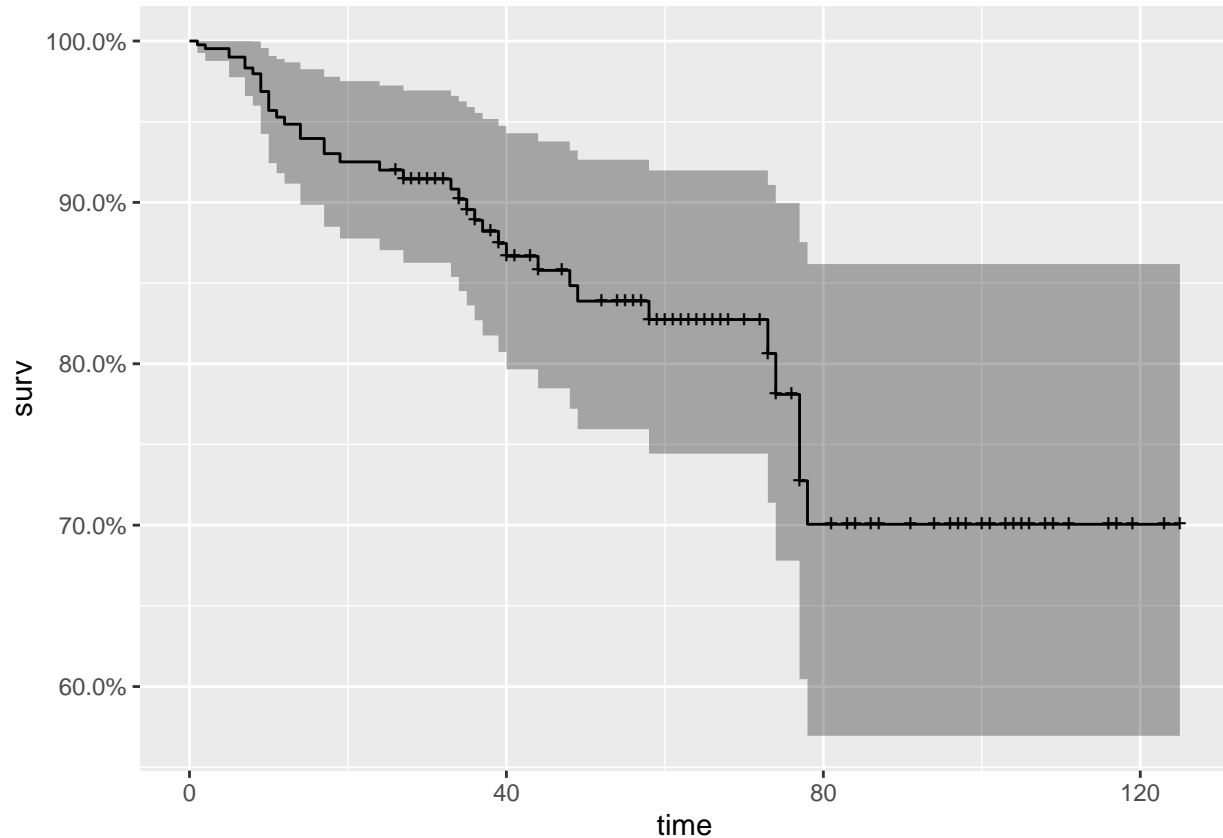
5.2 Cox Model

```
pc <- proc.time()
cox_all = coxph(Surv(time,recurrent)~., data=DATASET_TRAIN3,x=T,y=T)
proc.time() - pc
```



```
## user system elapsed
## 0.03 0.00 0.03

cox_fit <- survfit(cox_all)
autoplot(cox_fit)
```



```
cox_AIC = stepAIC(cox_all, trace=F)
summary(cox_AIC)
```

```
## Call:
## coxph(formula = Surv(time, recurrent) ~ radius_mean + perimeter_mean +
## area_mean + smoothness_mean + concavity_mean + fractal_dimension_mean +
## area_SD + compactness_SD + concave_points_SD + symmetry_SD +
## radius_worst + texture_worst + area_worst + compactness_worst +
## concavity_worst + Tumor_size, data = DATASET_TRAIN3, x = T,
## y = T)
##
## n= 127, number of events= 38
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## radius_mean    -2.497e+01  1.428e-11  6.387e+00 -3.910  9.24e-05
## perimeter_mean   1.992e+01  4.464e+08  6.178e+00  3.224  0.001264
## area_mean        6.009e+00  4.071e+02  2.239e+00  2.683  0.007290
## smoothness_mean  1.131e+00  3.098e+00  4.549e-01  2.486  0.012921
## concavity_mean  -2.065e+00  1.268e-01  9.191e-01 -2.247  0.024632
## fractal_dimension_mean -1.618e+00  1.982e-01  4.729e-01 -3.422  0.000621
## area_SD          1.680e+00  5.364e+00  5.883e-01  2.855  0.004303
```

```

## compactness_SD      6.385e-01  1.894e+00  4.212e-01  1.516  0.129522
## concave_points_SD   -1.165e+00  3.119e-01  4.211e-01 -2.767  0.005663
## symmetry_SD         4.498e-01  1.568e+00  2.572e-01  1.749  0.080361
## radius_worst        5.147e+00  1.719e+02  2.098e+00  2.453  0.014158
## texture_worst       3.895e-01  1.476e+00  2.390e-01  1.630  0.103191
## area_worst          -6.348e+00  1.750e-03  2.166e+00 -2.931  0.003381
## compactness_worst   -1.257e+00  2.844e-01  5.967e-01 -2.107  0.035130
## concavity_worst     1.309e+00  3.701e+00  6.139e-01  2.132  0.033043
## Tumor_size          3.464e-01  1.414e+00  1.532e-01  2.262  0.023724
##
## radius_mean          ***
## perimeter_mean       **
## area_mean            **
## smoothness_mean      *
## concavity_mean       *
## fractal_dimension_mean ***
## area_SD              **
## compactness_SD
## concave_points_SD    **
## symmetry_SD          .
## radius_worst         *
## texture_worst
## area_worst           **
## compactness_worst    *
## concavity_worst      *
## Tumor_size           *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##               exp(coef) exp(-coef) lower .95 upper .95
## radius_mean    1.428e-11  7.001e+10  5.227e-17  3.903e-06
## perimeter_mean  4.464e+08  2.240e-09  2.462e+03  8.091e+13
## area_mean      4.071e+02  2.456e-03  5.053e+00  3.280e+04
## smoothness_mean 3.098e+00  3.228e-01  1.270e+00  7.555e+00
## concavity_mean  1.268e-01  7.888e+00  2.093e-02  7.680e-01
## fractal_dimension_mean 1.982e-01  5.044e+00  7.847e-02  5.008e-01
## area_SD        5.364e+00  1.864e-01  1.693e+00  1.699e+01
## compactness_SD  1.894e+00  5.281e-01  8.295e-01  4.323e+00
## concave_points_SD 3.119e-01  3.206e+00  1.366e-01  7.120e-01
## symmetry_SD     1.568e+00  6.378e-01  9.471e-01  2.596e+00
## radius_worst    1.719e+02  5.819e-03  2.815e+00  1.049e+04
## texture_worst   1.476e+00  6.774e-01  9.241e-01  2.358e+00
## area_worst      1.750e-03  5.713e+02  2.509e-05  1.221e-01
## compactness_worst 2.844e-01  3.516e+00  8.831e-02  9.161e-01
## concavity_worst  3.701e+00  2.702e-01  1.111e+00  1.233e+01
## Tumor_size      1.414e+00  7.072e-01  1.047e+00  1.909e+00
##
## Concordance= 0.757 (se = 0.041 )
## Likelihood ratio test= 43.36 on 16 df,  p=2e-04
## Wald test              = 41.49 on 16 df,  p=5e-04
## Score (logrank) test = 46.72 on 16 df,  p=8e-05
cox_AIC$score
## [1] 46.72174

```

```
summary(survfit(cox_all), time=24)

## Call: survfit(formula = cox_all)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    24   107     21    0.92   0.026      0.87      0.972

summary(survfit(cox_AIC), time=24)

## Call: survfit(formula = cox_AIC)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    24   107     21   0.904  0.0271      0.853      0.959
```

The survival probability at time 24 is approximately 92%.

5.2.1 AUC Cox Model

```
lp <- predict(cox_AIC)
lpnew <- predict(cox_AIC, newdata=DATASET_TEST3)
Surv.rsp <- Surv(DATASET_TRAIN3$time, DATASET_TRAIN3$recurrent)
Surv.rsp.new <- Surv(DATASET_TEST3$time, DATASET_TEST3$recurrent)
times <- seq(10, 1000, 10)

AUC_CD.cox <- AUC.cd(Surv.rsp, Surv.rsp.new, lp, lpnew, times)
auc.cox <- AUC_CD.cox[3]
print(paste0("AUC Cox Model : ", auc.cox))

## [1] "AUC Cox Model : 0.856123737622364"

auc.cox <- 0.856123737622364
```

5.3 Survival Random Forests

```
pc <- proc.time()
rf_surv = rfsrc(Surv(time,recurrent)~radius_mean + perimeter_mean +
  area_mean + smoothness_mean + concavity_mean + fractal_dimension_mean +
  area_SD + compactness_SD + concave_points_SD + symmetry_SD +
  radius_worst + texture_worst + area_worst + compactness_worst +
  concavity_worst + Tumor_size,DATASET_TRAIN3)
proc.time() -pc

##      user  system elapsed
##    3.65    0.53    0.72

rf_surv

##                      Sample size: 127
##                      Number of deaths: 38
##                      Number of trees: 1000
##                      Forest terminal node size: 15
##                      Average no. of terminal nodes: 6.139
## No. of variables tried at each split: 4
##                      Total no. of variables: 16
##                      Resampling used to grow trees: swor
##                      Resample size used to grow trees: 80
##                      Analysis: RSF
```

```
##                      Family: surv
##          Splitting rule: logrank *random*
##      Number of random split points: 10
##                      Error rate: 42.21%

pred_rf=predict(rf_surv,DATASET_TEST3,outcome="test")
pred_rf

##      Sample size of test (predict) data: 31
##          Number of deaths in test data: 9
##          Number of grow trees: 1000
##      Average no. of grow terminal nodes: 6.139
##          Total no. of grow variables: 16
##          Resampling used to grow trees: swor
##      Resample size used to grow trees: 20
##          Analysis: RSF
##          Family: surv
##          Test set error rate: 38.03%
```

5.3.1 AUC Survival Random Forests

```
w.ROC1 = risksetAUC(Stime = DATASET_TEST3$time,
                    status = DATASET_TEST3$recurrent,
                    marker = pred_rf$predicted.oob, tmax = 250, plot = F)

w.ROC1

## $utimes
## [1]  1  3  4  8 11 12 16 19 26
##
## $St
## [1] 0.9677419 0.9354839 0.9032258 0.8709677 0.8387097 0.8064516 0.7741935
## [8] 0.7419355 0.7096774
##
## $AUC
## [1] 0.5758698 0.5829044 0.5909609 0.5755421 0.5776602 0.5735938 0.5700098
## [8] 0.5816028 0.5574550
##
## $Cindex
## [1] 0.5766965

print (paste0("Survival probability at time ", 24," is between ",w.ROC1$St[9]," and ",w.ROC1$St[8]))
## [1] "Survival probability at time 24 is between 0.709677419354839 and 0.741935483870968"

print (paste0("AUC Survival Random Forests1 : ", w.ROC1$Cindex))
## [1] "AUC Survival Random Forests1 : 0.576696507918134"

auc.srf <- 0.576696507918134
```

5.4 Cox Boost Model

```
pc <- proc.time()
coxboost_surv = iCoxBoost(Surv(time,recurrent) ~.,data=DATASET_TRAIN3)
proc.time() -pc

##      user  system elapsed
```

```
##      3.34      0.00      3.36
summary(coxboost_surv)

## 8 boosting steps resulting in 3 non-zero coefficients
## partial log-likelihood: -166.8915
##
## Optional covariates with non-zero coefficients at boosting step 8:
## parameter estimate > 0:
##   area_mean, perimeter_worst, Tumor_size
## parameter estimate < 0:
##

pc <- proc.time()
coxboost_surv = iCoxBoost(Surv(time,recurrent) ~ radius_mean + perimeter_mean +
  area_mean + smoothness_mean + concavity_mean + fractal_dimension_mean +
  area_SD + compactness_SD + concave_points_SD + symmetry_SD +
  radius_worst + texture_worst + area_worst + compactness_worst +
  concavity_worst + Tumor_size,data=DATASET_TRAIN3)
proc.time() - pc

##      user      system elapsed
##      2.89       0.00       2.89

summary(coxboost_surv)

## 10 boosting steps resulting in 3 non-zero coefficients
## partial log-likelihood: -166.4092
##
## Optional covariates with non-zero coefficients at boosting step 10:
## parameter estimate > 0:
##   area_mean, Tumor_size
## parameter estimate < 0:
##   fractal_dimension_mean
```

5.4.1 AUC Cox Boost Model

```
lp2 <- predict(coxboost_surv)
lpnew2 <- predict(coxboost_surv, newdata=DATASET_TEST3)
Surv.rsp2 <- Surv(DATASET_TRAIN3$time, DATASET_TRAIN3$recurrent)
Surv.rsp.new2 <- Surv(DATASET_TEST3$time, DATASET_TEST3$recurrent)
times2 <- seq(10, 1000, 10)

AUC_CD.coxboost <- AUC.cd(Surv.rsp2, Surv.rsp.new2, lp2, lpnew2, times2)
auc.coxboost <- AUC_CD.coxboost[3]
print(paste0("AUC Cox Boost Model : ", auc.coxboost))

## [1] "AUC Cox Boost Model : 0.567571015744152"

auc.coxboost <- 0.567571015744152
```

5.5 Cox Robust Model

```
pc <- proc.time()
coxrobust_surv = coxr(Surv(time,recurrent) ~.,data=DATASET_TRAIN3)
summary(coxrobust_surv)

##              Length Class  Mode
## coefficients      32  -none- numeric
```

```

## ple.coefficients    32    -none- numeric
## lambda             127    -none- numeric
## lambda.ple         127    -none- numeric
## var                1024   -none- numeric
## var.ple            1024   -none- numeric
## wald.test           1     -none- numeric
## ewald.test          1     -none- numeric
## skip                0     -none- numeric
## call                3     -none- call
## terms               3     terms call
## x                   4064   -none- numeric
## y                   127    Surv   numeric

pc <- proc.time()
coxrobust_surv = coxr(Surv(time,recurrent) ~ radius_mean + perimeter_mean +
  area_mean + smoothness_mean + concavity_mean + fractal_dimension_mean +
  area_SD + compactness_SD + concave_points_SD + symmetry_SD +
  radius_worst + texture_worst + area_worst + compactness_worst +
  concavity_worst + Tumor_size,data=DATASET_TRAIN3)
proc.time() - pc

##      user  system elapsed
##    0.06    0.00    0.06

summary(coxrobust_surv)

##              Length Class  Mode
## coefficients      16    -none- numeric
## ple.coefficients   16    -none- numeric
## lambda            127    -none- numeric
## lambda.ple        127    -none- numeric
## var               256    -none- numeric
## var.ple           256    -none- numeric
## wald.test          1     -none- numeric
## ewald.test         1     -none- numeric
## skip               0     -none- numeric
## call               3     -none- call
## terms              3     terms call
## x                  2032   -none- numeric
## y                  127    Surv   numeric

```

5.5.1 AUC Cox Robust Model

```

lp3 <- predict(coxrobust_surv)
Surv.rsp3 <- Surv(DATASET_TRAIN3$time, DATASET_TRAIN3$recurrent)
Surv.rsp.new3 <- Surv(DATASET_TEST3$time, DATASET_TEST3$recurrent)
times3 <- seq(10, 1000, 10)

AUC_CD.coxrobust <- AUC.cd(Surv.rsp3, Surv.rsp.new3, lp3, lp3, times3)
auc.coxrobust <- AUC_CD.coxrobust[3]
print(paste0("AUC Cox Robust Model : ", auc.coxrobust))

## [1] "AUC Cox Robust Model : 0.813890605104405"

auc.coxrobust <- 0.813890605104405

```

6 Model comparison and Conclusion

6.1 Model Comparison

```
modelsclass <- c('randomforest', 'knn', 'naiveBayes', 'logreg')
modelssurv <- c('cox', 'srf', 'boostcox', 'robustcox')
aucmodelsclass <- c(auc.forest, auc.knn, auc.naiveBayes, auc.logistic)
aucmodelssurv <- c(auc.cox, auc.srf, auc.coxboost, auc.coxrobust)
resultsclass <- data.frame("Models Classifiers" = modelsclass, "AUC Classifiers" = aucmodelsclass)
resultssurv <- data.frame("Models Survival" = modelssurv, "AUC Survival" = aucmodelssurv)

resultfinal <- cbind(resultsclass, resultssurv)
# Table comparison
kable(arrange(resultfinal, desc(aucmodelsclass), desc(aucmodelssurv)), digits = 2) %>%
  kable_styling(bootstrap_options = c("striped", "hover"),
                full_width = F,
                font_size = 12,
                position = "left")
```

Models.Classifiers	AUC.Classifiers	Models.Survival	AUC.Survival
randomforest	0.88	cox	0.86
logreg	0.86	robustcox	0.81
naiveBayes	0.79	boostcox	0.57
knn	0.77	srf	0.58

6.2 Conclusion

From the results of the different models we have had, it seems that **the random forest for classification** model gives better results with an AUC of **0.88** and could be used for prediction for new observations. However, the **cox** model makes a good prediction with an AUC of **0.86**.
