

Bank Marketing Project

```
### Importing Data ###

setwd("~/Downloads/ML/bank-additional")

# Importing the csv file and keeping stringsAsFactors= T for automatically converting all
# the string variables into factors
bank <- read.table("bank-additional-full.csv",header=TRUE,sep=";")
str(bank)

## 'data.frame':    41188 obs. of  21 variables:
## $ age           : int  56 57 37 40 56 45 59 41 24 25 ...
## $ job           : Factor w/ 12 levels "admin.," "blue-collar",...: 4 8 8 1 8 8 1 2 10 8 ...
## $ marital       : Factor w/ 4 levels "divorced","married",...: 2 2 2 2 2 2 2 2 3 3 ...
## $ education     : Factor w/ 8 levels "basic.4y","basic.6y",...: 1 4 4 2 4 3 6 8 6 4 ...
## $ default       : Factor w/ 3 levels "no","unknown",...: 1 2 1 1 1 2 1 2 1 1 ...
## $ housing       : Factor w/ 3 levels "no","unknown",...: 1 1 3 1 1 1 1 1 3 3 ...
## $ loan          : Factor w/ 3 levels "no","unknown",...: 1 1 1 1 3 1 1 1 1 1 ...
## $ contact       : Factor w/ 2 levels "cellular","telephone": 2 2 2 2 2 2 2 2 2 2 ...
## $ month         : Factor w/ 10 levels "apr","aug","dec",...: 7 7 7 7 7 7 7 7 7 7 ...
## $ day_of_week   : Factor w/ 5 levels "fri","mon","thu",...: 2 2 2 2 2 2 2 2 2 2 ...
## $ duration      : int  261 149 226 151 307 198 139 217 380 50 ...
## $ campaign      : int  1 1 1 1 1 1 1 1 1 1 ...
## $ pdays         : int  999 999 999 999 999 999 999 999 999 999 ...
## $ previous      : int  0 0 0 0 0 0 0 0 0 0 ...
## $ poutcome      : Factor w/ 3 levels "failure","nonexistent",...: 2 2 2 2 2 2 2 2 2 2 ...
## $ emp.var.rate  : num  1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 ...
## $ cons.price.idx: num  94 94 94 94 94 ...
## $ cons.conf.idx : num  -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 ...
## $ euribor3m     : num  4.86 4.86 4.86 4.86 4.86 ...
## $ nr.employed   : num  5191 5191 5191 5191 5191 ...
## $ y             : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...

### Exploratory Data Analysis ###

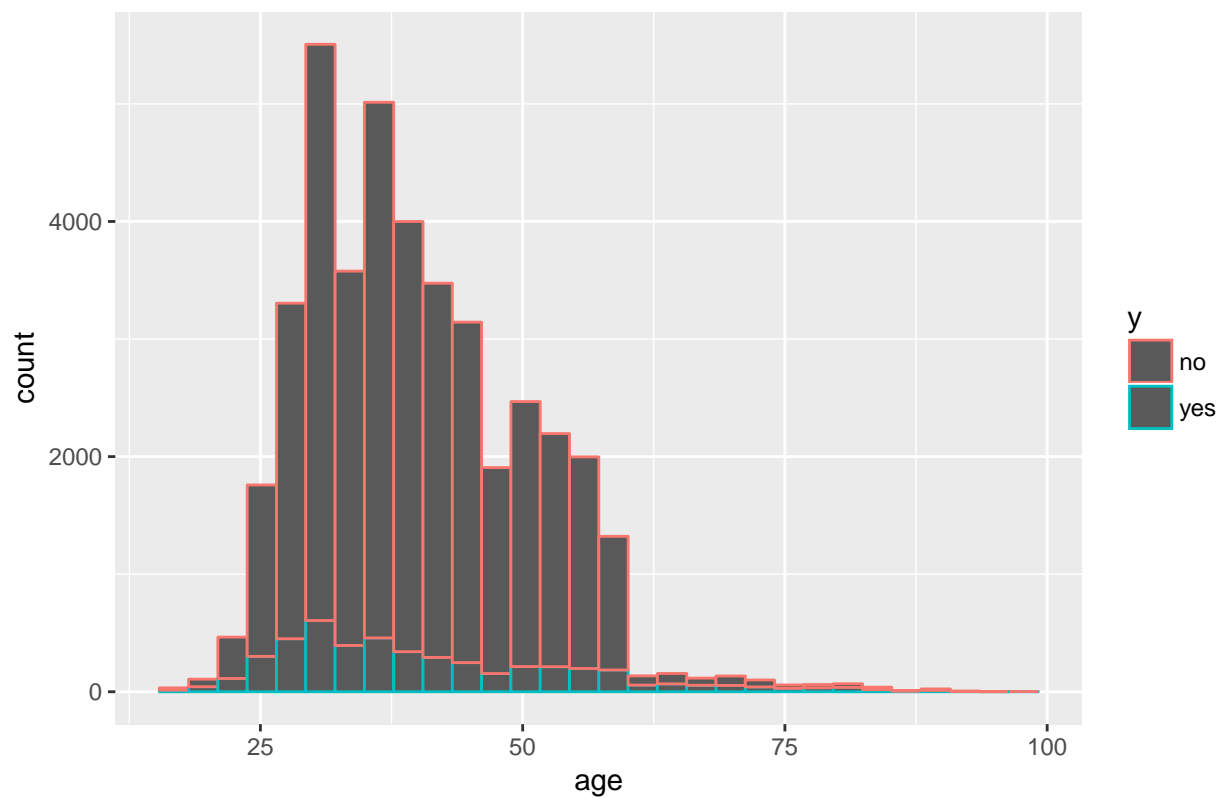
# Visualizing different variables in the data set and their relations with the dependent
# variable y

library(ggplot2)

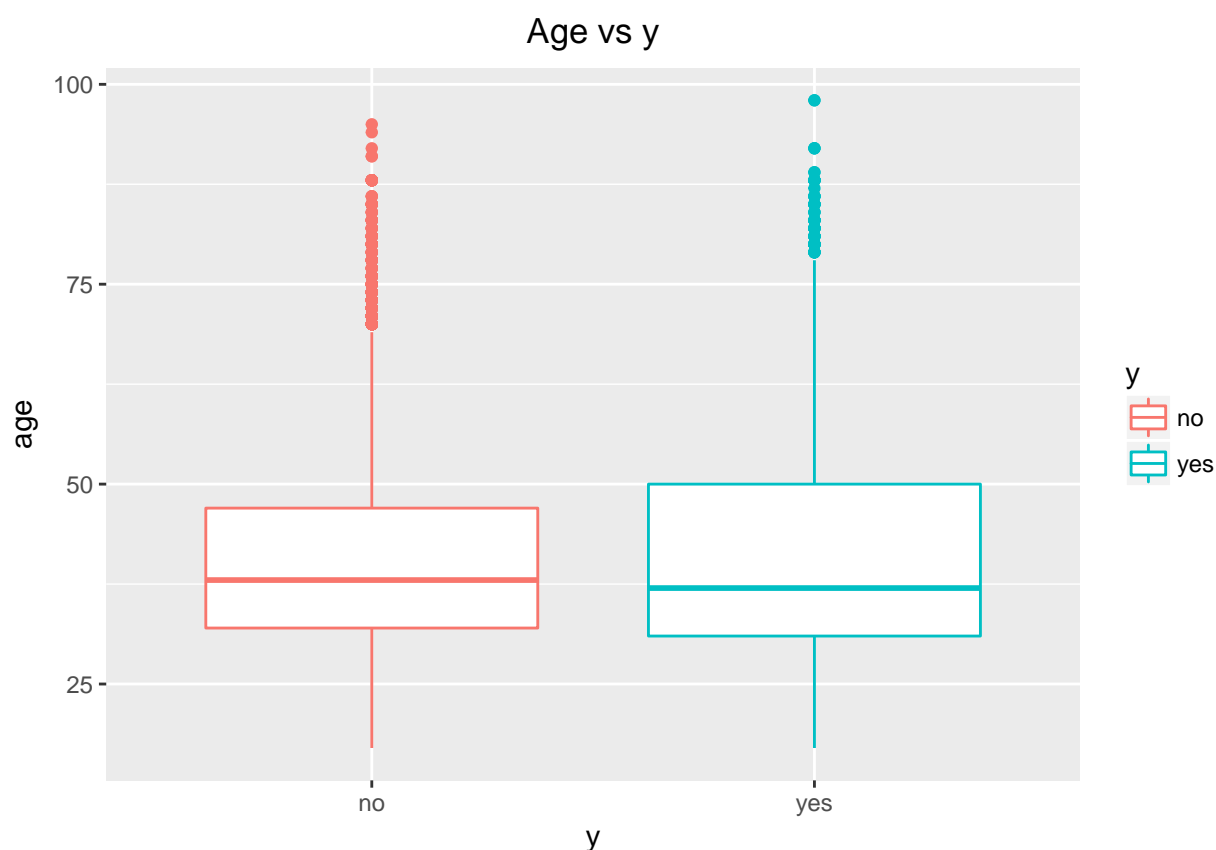
## The variable age shows that most of the people are between 25 and 60 as expected and it
# is slightly right skewed. And the distribution of people who subscribed is almost evenly
# distributed with respect to the number of people in that age group. ##
ggplot(data=bank, aes(x=age, col=y))+
  geom_histogram()+
  ggtitle("Age distribution based on subscription")+
  theme(plot.title = element_text(hjust = 0.5))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

Age distribution based on subscription



```
# A boxplot of "age vs y" also reflects the same information
ggplot(bank, aes(x=y, y=age, col=y))+
  geom_boxplot()+
  ggtitle("Age vs y")+
  theme(plot.title = element_text(hjust = 0.5))
```



```
## Creating a table to visualize the relationship between the job role of a person and
# variable y indicating whether a person subscribed for the plan or not
table(bank$job, bank$y)
```

```
##
##           no  yes
## admin.      9070 1352
## blue-collar 8616 638
## entrepreneur 1332 124
## housemaid    954 106
## management   2596 328
## retired      1286 434
## self-employed 1272 149
## services     3646 323
## student       600 275
## technician   6013 730
## unemployed    870 144
## unknown      293 37
```

```
# Lets look at the proportion of people subscribing with respect to their job roles
prop.table(table(bank$job, bank$y), 1)
```

```
##
##           no      yes
## admin.      0.87027442 0.12972558
## blue-collar 0.93105684 0.06894316
## entrepreneur 0.91483516 0.08516484
## housemaid    0.90000000 0.10000000
## management   0.88782490 0.11217510
## retired      0.74767442 0.25232558
## self-employed 0.89514426 0.10485574
```

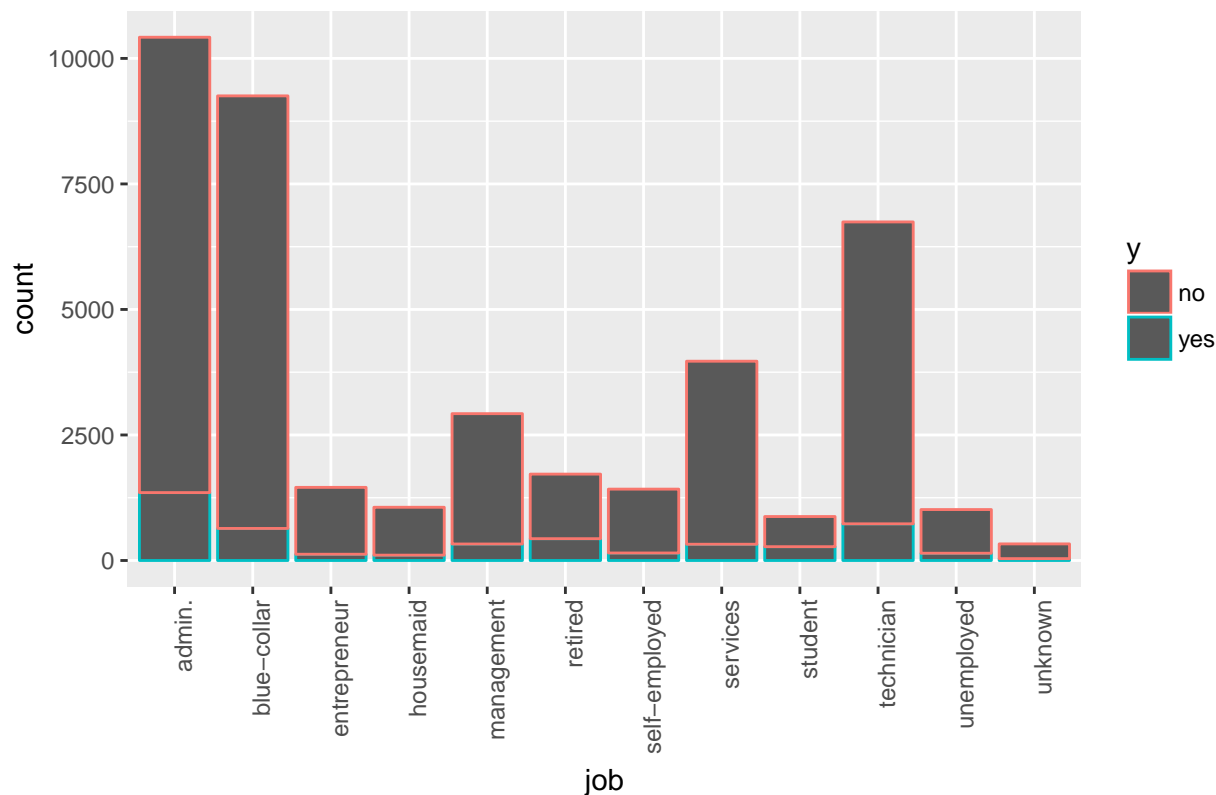
```
## services      0.91861930 0.08138070
## student       0.68571429 0.31428571
## technician    0.89173958 0.10826042
## unemployed    0.85798817 0.14201183
## unknown       0.88787879 0.11212121
```

*# Plotting the proportions of each category shows that students and retired people have
very high probability of saying "yes" to the subscription compared to all other
categories. And blue-collar, entrepreneur and services are the least probable categories
for saying "yes". ##*

```
ggplot(bank, aes(x=job, col=y))+
  geom_histogram(stat="count")+
  theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggtitle("Histogram of job in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

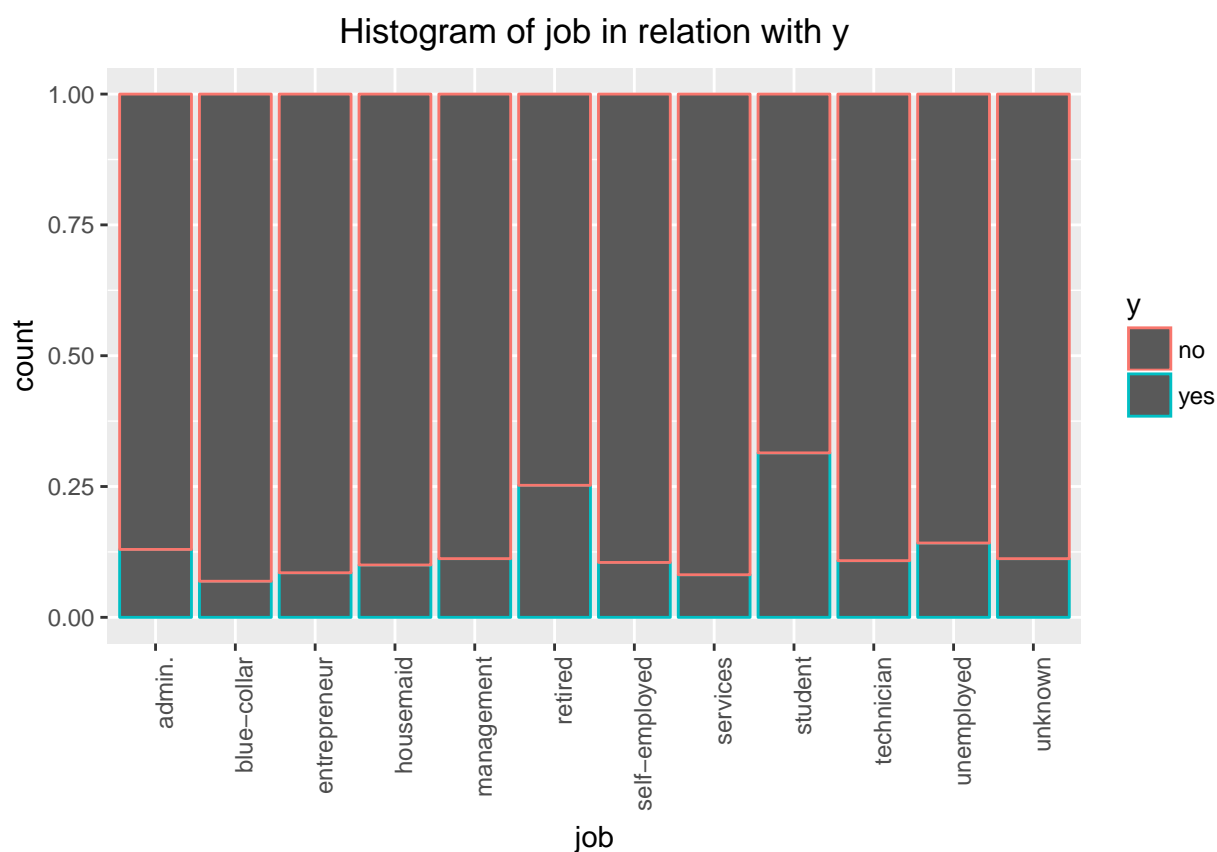
Warning: Ignoring unknown parameters: binwidth, bins, pad

Histogram of job in relation with y



```
ggplot(bank, aes(x=job, col=y))+
  geom_histogram(stat="count", position = "fill")+
  theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggtitle("Histogram of job in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad

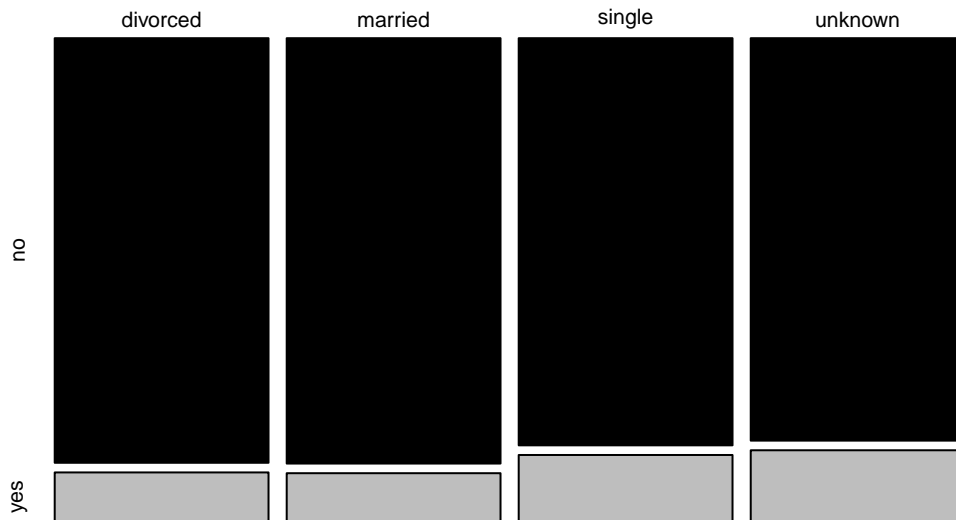


```
## A similar plot of proportions for marital status vs y shows the spread of y is almost
# evenly distributed and there is very little to no insight ##
prop.table(table(bank$marital, bank$y), 1)
```

```
##
##           no      yes
## divorced 0.8967910 0.1032090
## married  0.8984275 0.1015725
## single   0.8599585 0.1400415
## unknown  0.8500000 0.1500000
```

```
plot((prop.table(table(bank$marital, bank$y), 1)),
     main="Marital status vs y", col=c("black","grey"))
```

Marital status vs y

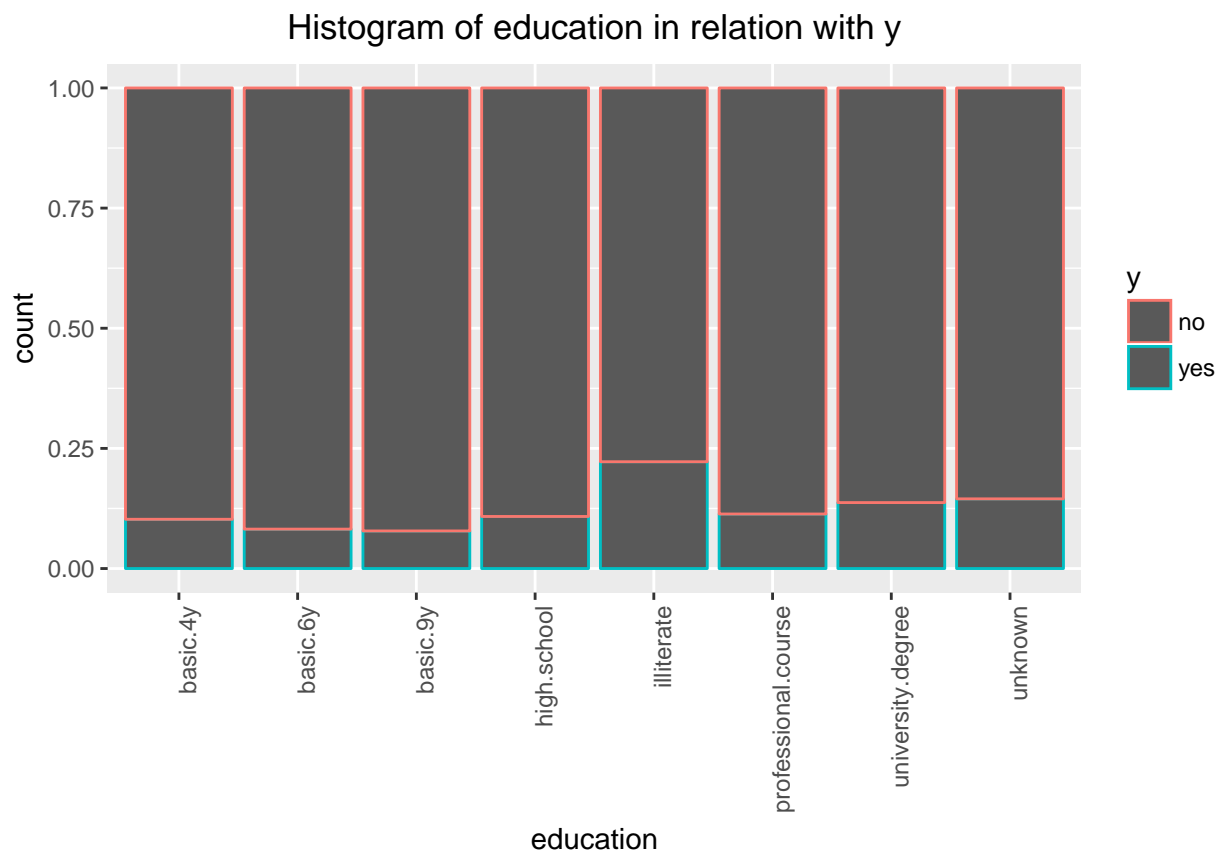


```
## The plot of proportions shows that people who are illiterate, people who has a
# university degree and the unknown category has more chance of taking the subscription
prop.table(table(bank$education, bank$y), 1)
```

```
##
##              no      yes
## basic.4y      0.89750958 0.10249042
## basic.6y      0.91797557 0.08202443
## basic.9y      0.92175352 0.07824648
## high.school   0.89164477 0.10835523
## illiterate    0.77777778 0.22222222
## professional.course 0.88651535 0.11348465
## university.degree 0.86275477 0.13724523
## unknown      0.85499711 0.14500289
```

```
ggplot(bank, aes(x=education, col=y))+
  geom_histogram(stat="count", position = "fill")+
  theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggtitle("Histogram of education in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

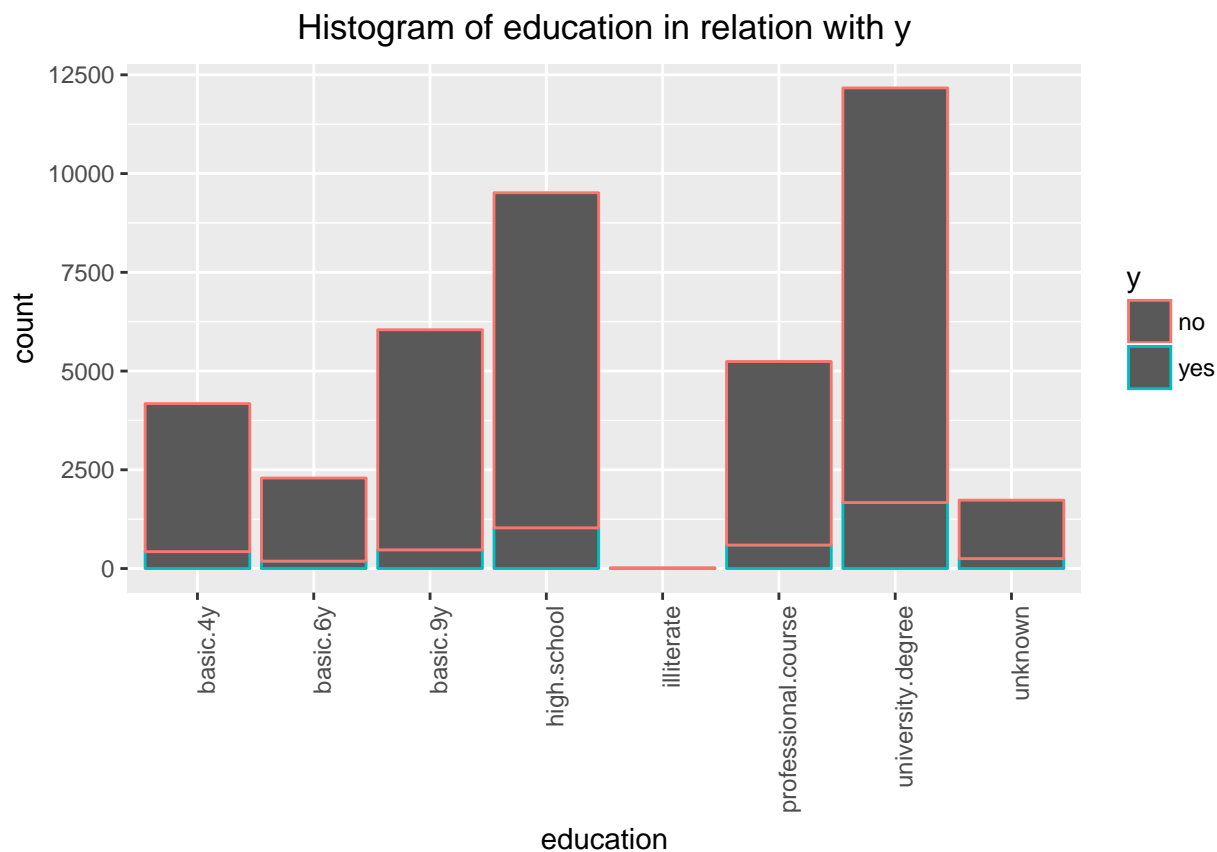
```
## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



*# But histogram of education shows that concentration of people who are illiterate is very
small compared to other categories. So people having a university degree are more
reasonable target.*

```
ggplot(bank, aes(x=education, col=y))+
  geom_histogram(stat="count")+
  theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggtitle("Histogram of education in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad



*# The default variable is very less informative as it has only 3 values in the category of
people who have defaulted and also large number of unknown values. So we can't get any
understanding of its relation with y*

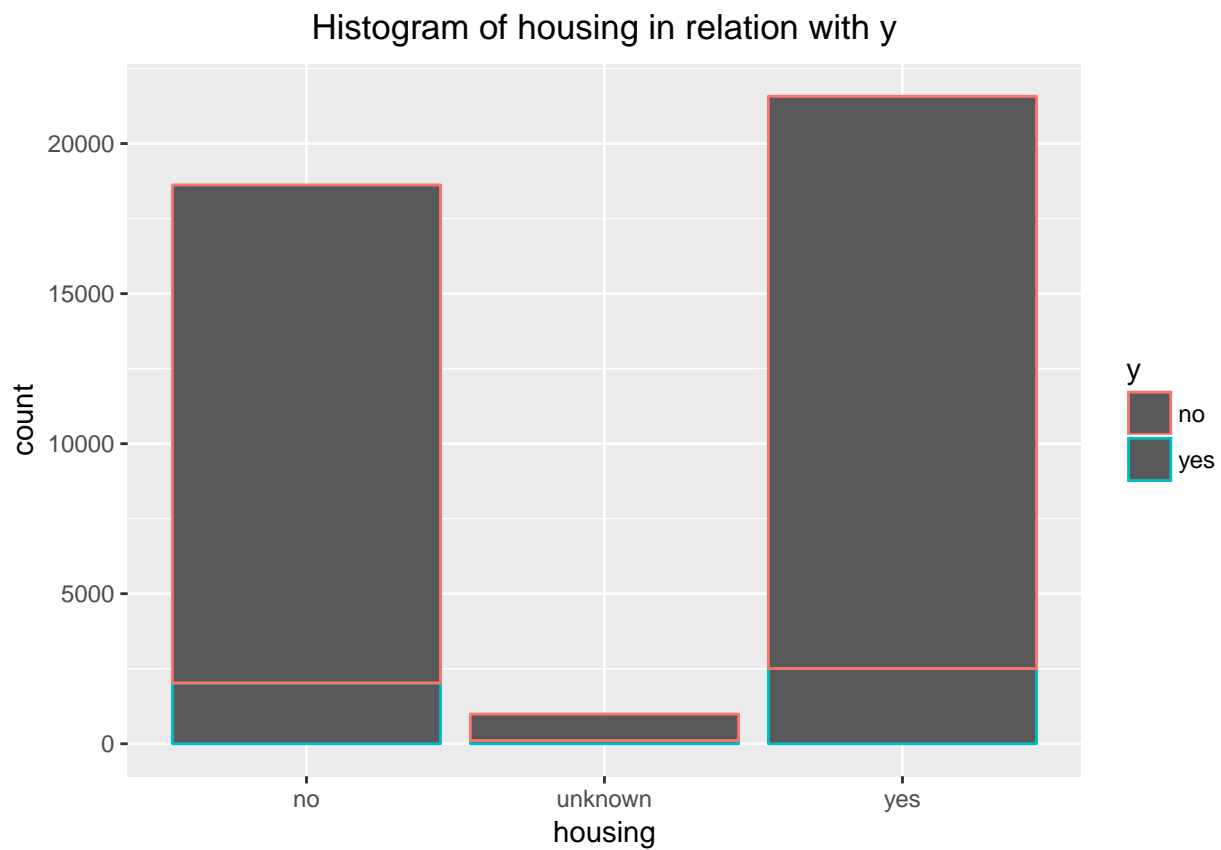
```
table(bank$default)
```

```
##
##      no unknown      yes
## 32588    8597         3
```

*# The proportion plots show that the variable y is almost uniformly distributed in all the
3 categories of both housing and loan variables which indicates that these variables has
very less correlation with variable y*

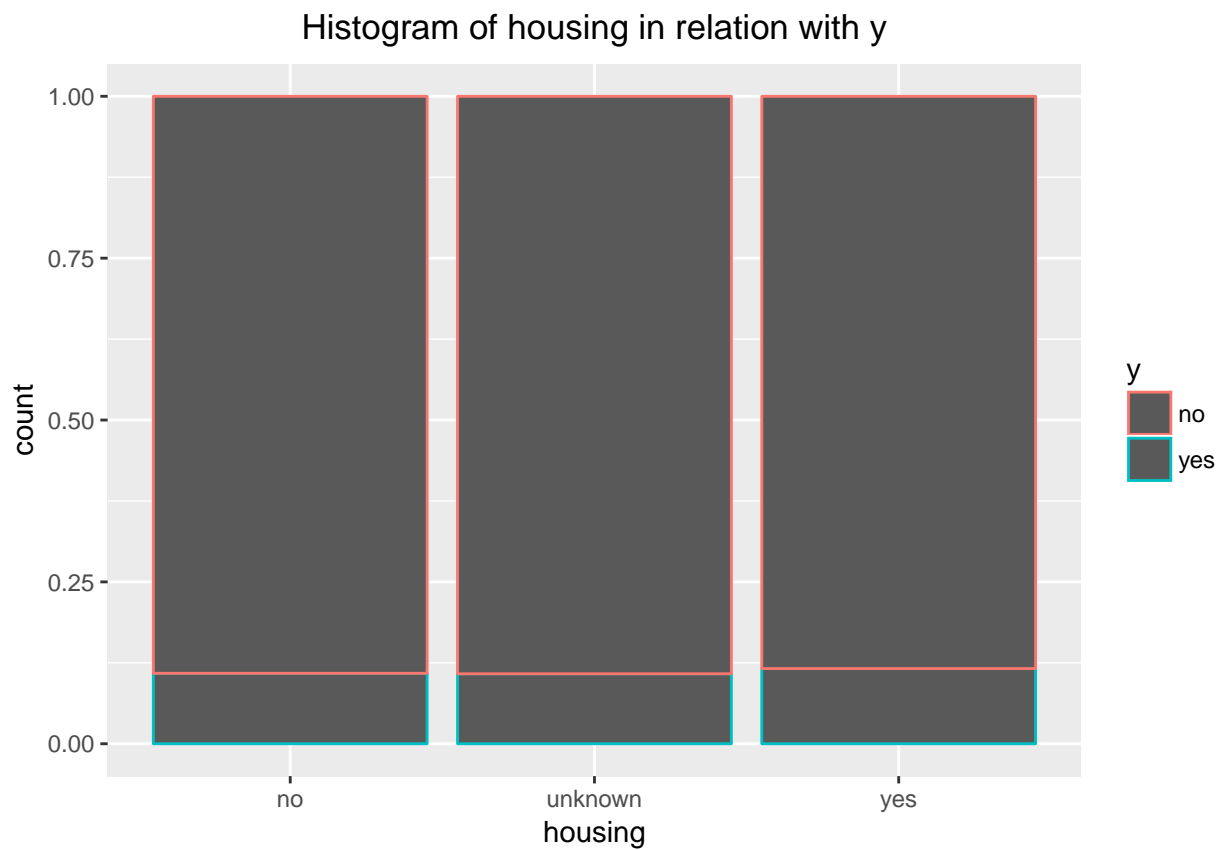
```
ggplot(bank, aes(x=housing, col=y))+
  geom_histogram(stat="count")+
  ggtitle("Histogram of housing in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

```
## Warning: Ignoring unknown parameters: binwidth, bins, pad
```

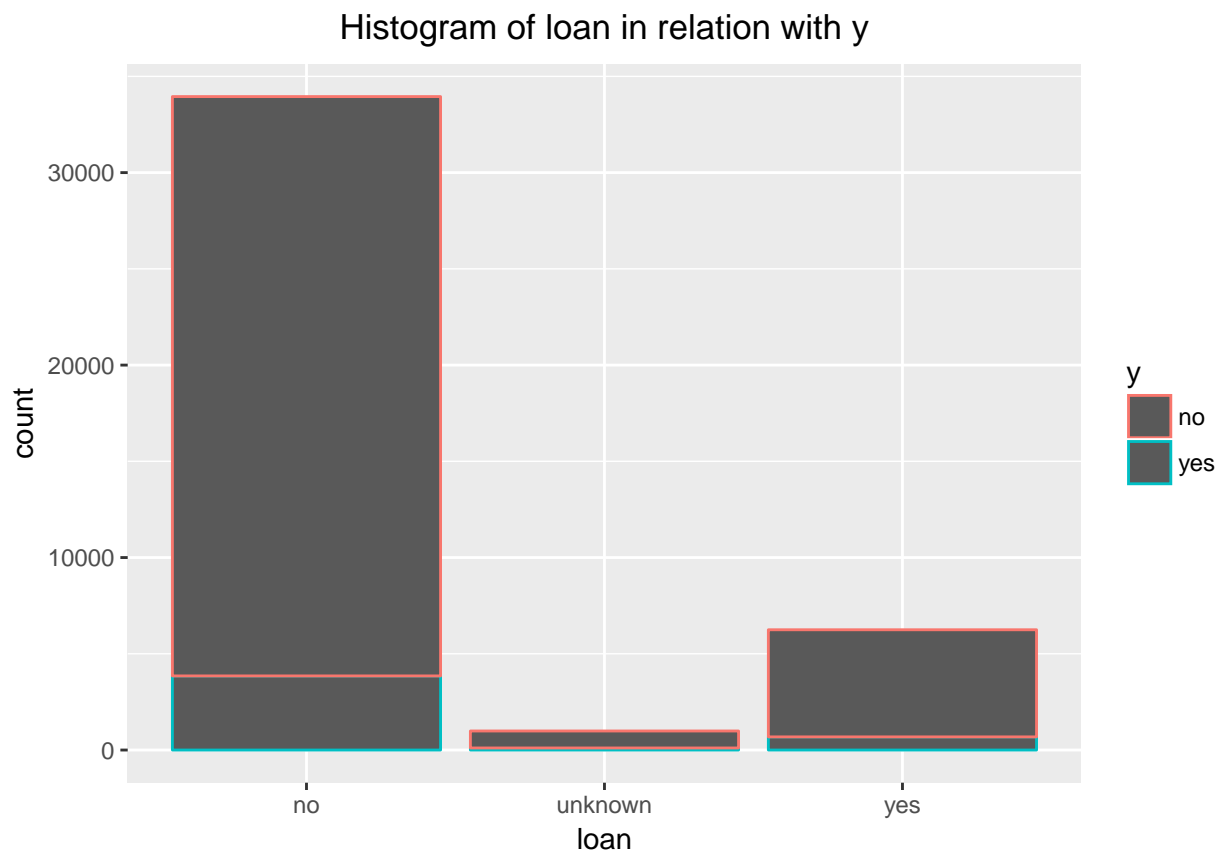
```
ggplot(bank, aes(x=housing, col=y))+  
  geom_histogram(stat="count", position = "fill")+  
  ggtitle("Histogram of housing in relation with y")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad



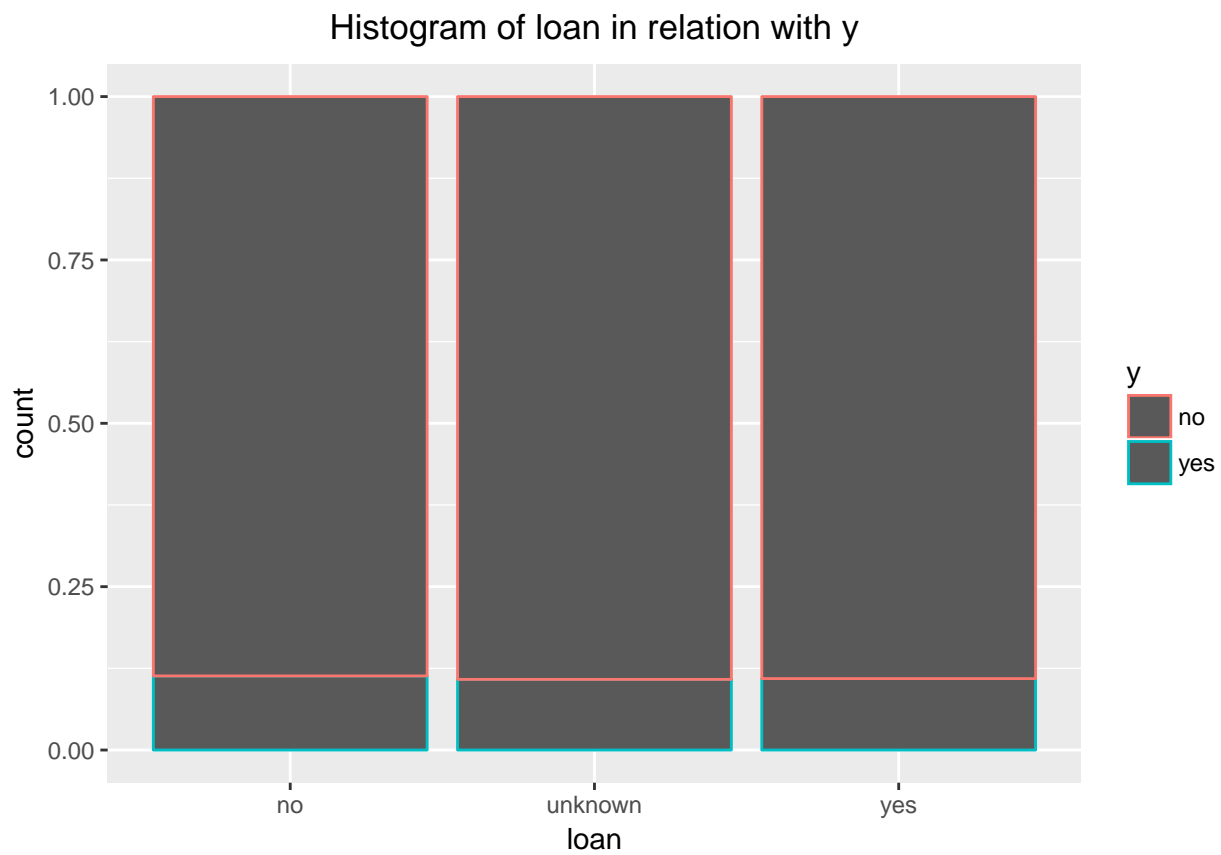
```
ggplot(bank, aes(x=loan, col=y))+  
  geom_histogram(stat="count")+  
  ggtitle("Histogram of loan in relation with y")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad

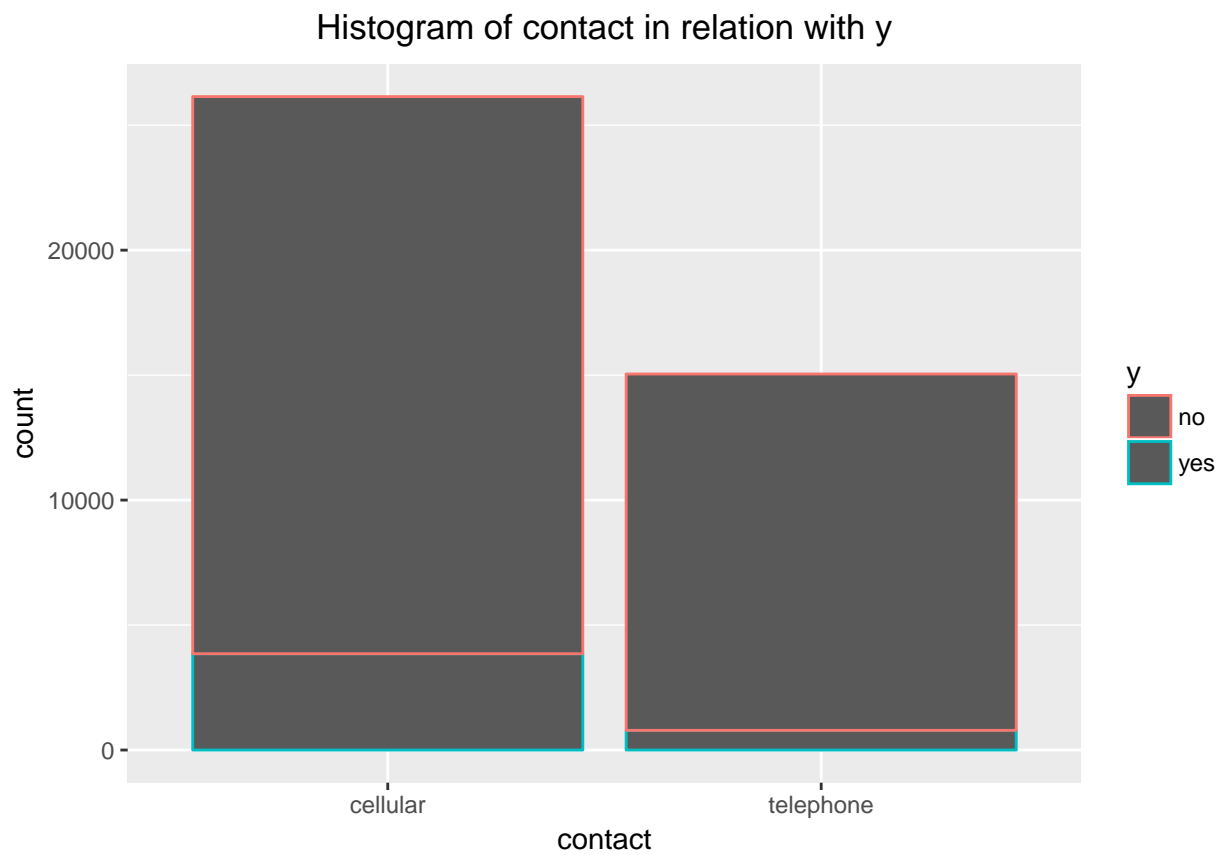


```
ggplot(bank, aes(x=loan, col=y))+  
  geom_histogram(stat="count", position = "fill")+  
  ggtitle("Histogram of loan in relation with y")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad

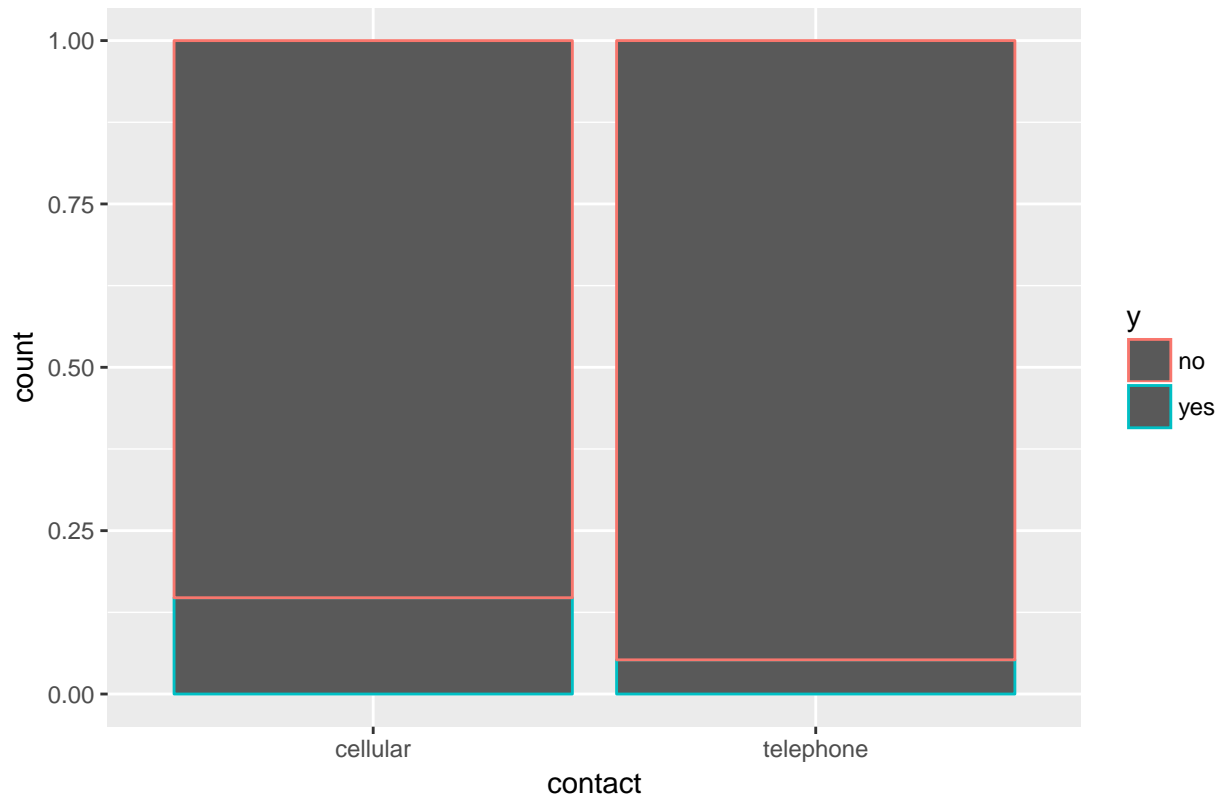


```
# The people who were contacted through cellular phone have slightly high probability of  
# taking the plan compared to the people who were contacted through a telephone  
ggplot(bank, aes(x=contact, col=y))+  
  geom_bar()+  
  ggtitle("Histogram of contact in relation with y")+  
  theme(plot.title = element_text(hjust = 0.5))
```



```
ggplot(bank, aes(x=contact, col=y))+  
  geom_bar(position = "fill")+  
  ggtitle("Histogram of contact in relation with y")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of contact in relation with y

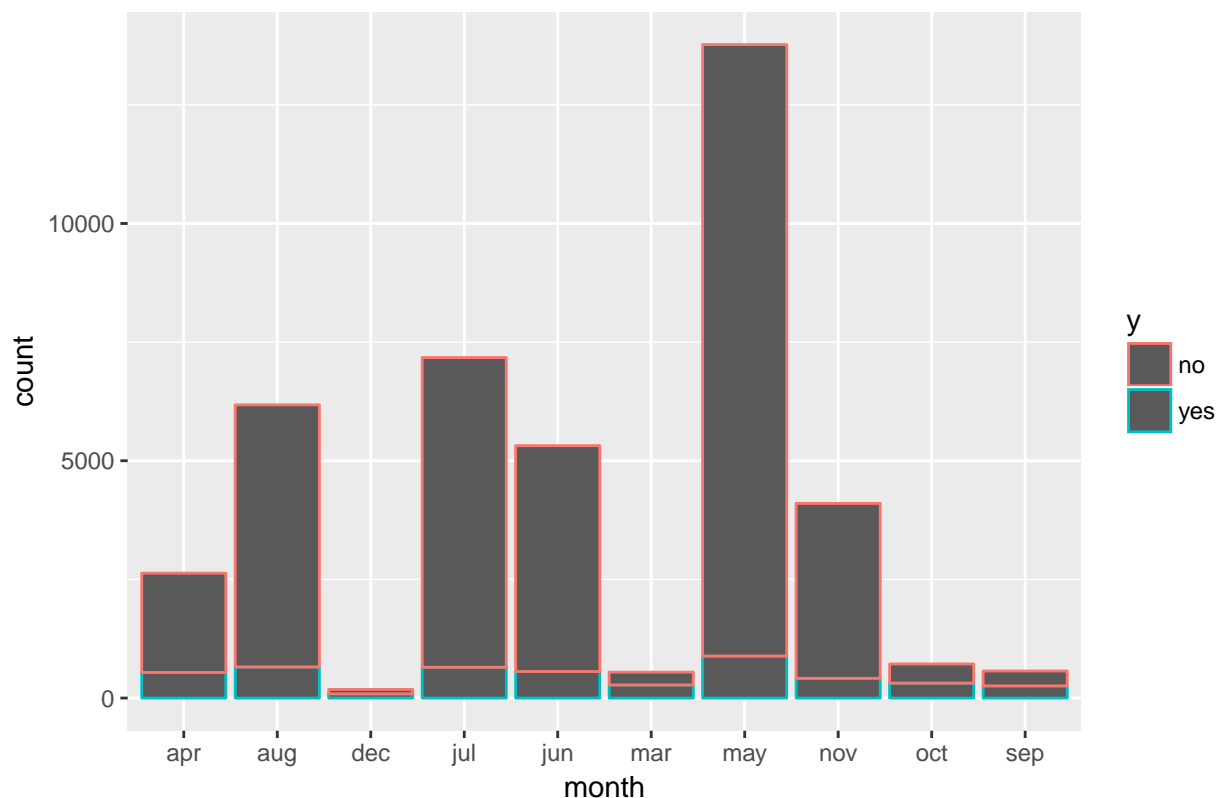


*# The plot of proportion table and scatterplot of month and day of the week on which
people were contacted shows that the months december, march, october and september
have a very high probability of people taking the plan compared to other months.
But the histogram of month in accordance with y shows that very less number of people
were actually contacted in those months.*

```
ggplot(bank, aes(x=month, col=y))+
  geom_histogram(stat="count")+
  ggtitle("Histogram of month in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Ignoring unknown parameters: binwidth, bins, pad

Histogram of month in relation with y



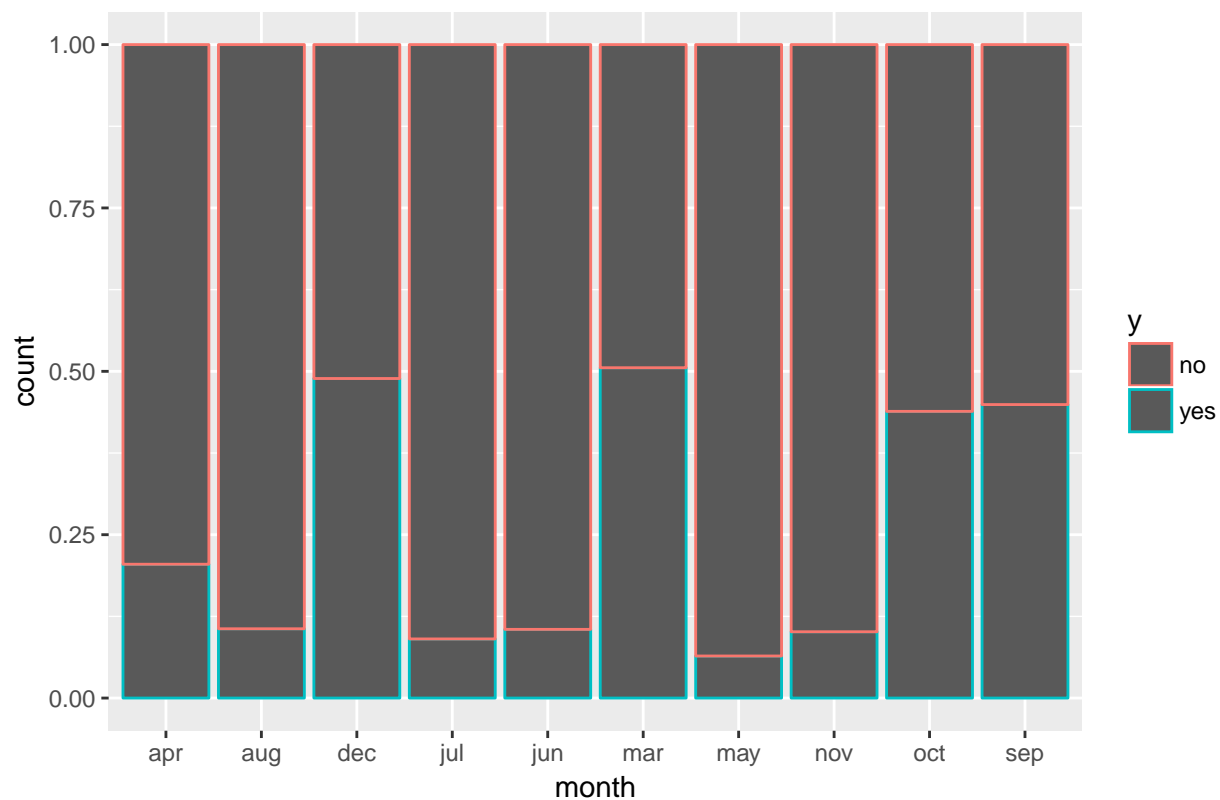
```
prop.table(table(bank$month, bank$y),1)
```

```
##
##           no           yes
## apr 0.79521277 0.20478723
## aug 0.89397863 0.10602137
## dec 0.51098901 0.48901099
## jul 0.90953443 0.09046557
## jun 0.89488530 0.10511470
## mar 0.49450549 0.50549451
## may 0.93565255 0.06434745
## nov 0.89856133 0.10143867
## oct 0.56128134 0.43871866
## sep 0.55087719 0.44912281
```

```
ggplot(bank, aes(x=month, col=y))+
  geom_histogram(stat="count", position = "fill")+
  ggtitle("Histogram of month in relation with y")+
  theme(plot.title = element_text(hjust = 0.5))
```

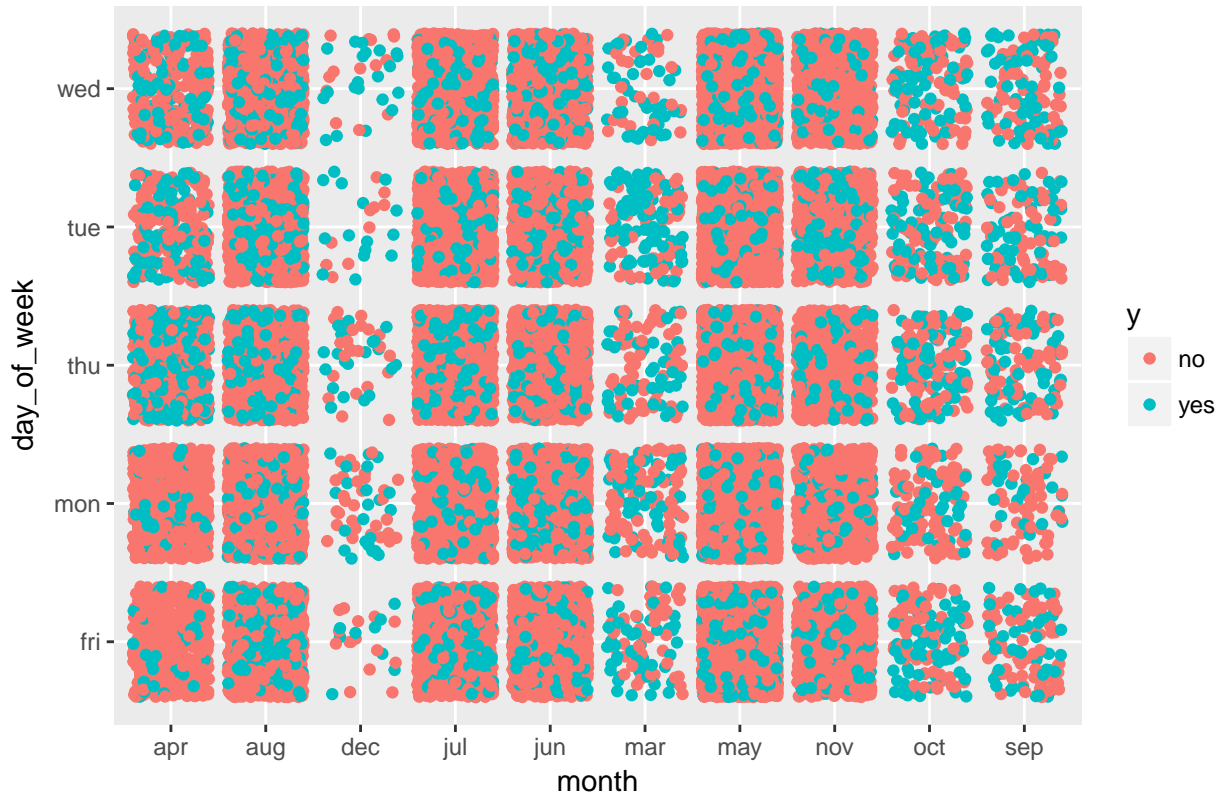
```
## Warning: Ignoring unknown parameters: binwidth, bins, pad
```

Histogram of month in relation with y



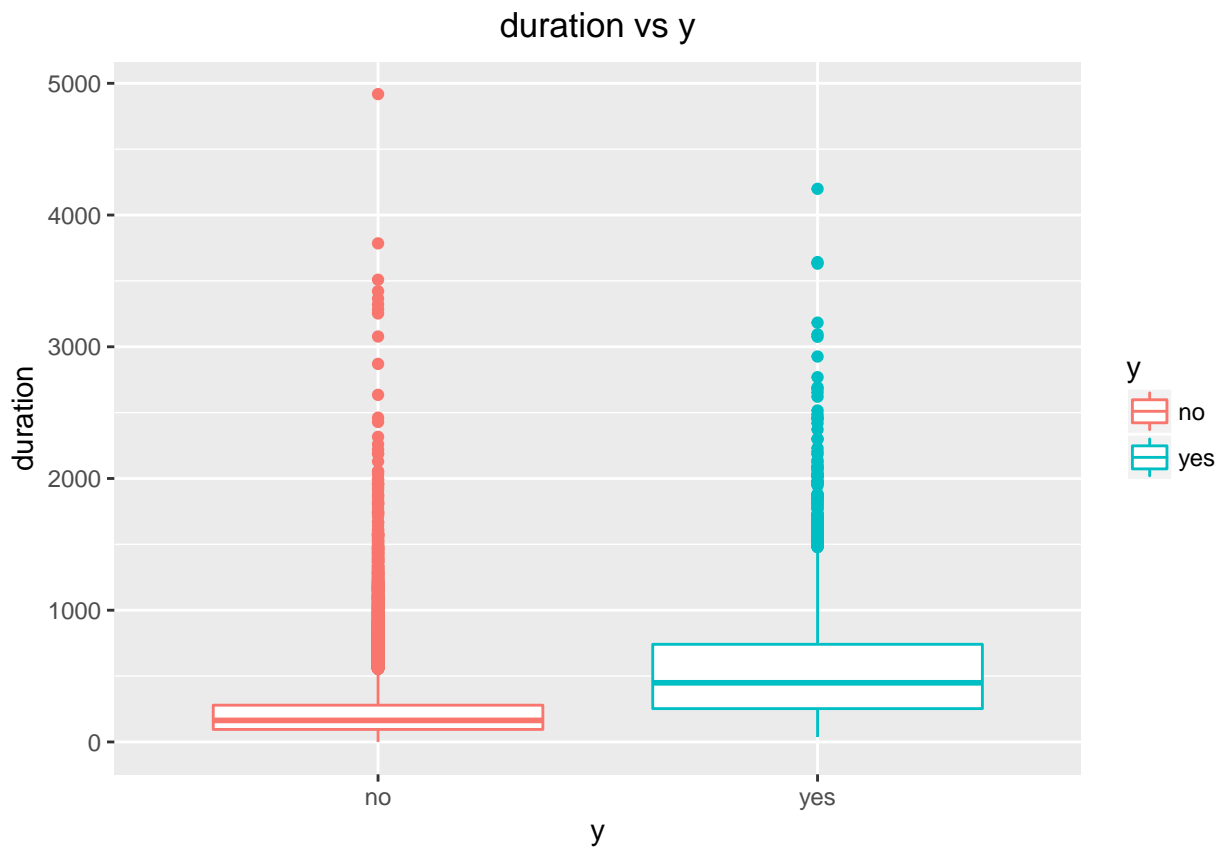
```
ggplot(bank, aes(x=month, y=day_of_week, col=y)) +
  geom_jitter()+
  ggtitle("Scatter plot of month and day of week wrt y")+
  theme(plot.title = element_text(hjust = 0.5))
```


Scatter plot of month and day of week wrt y

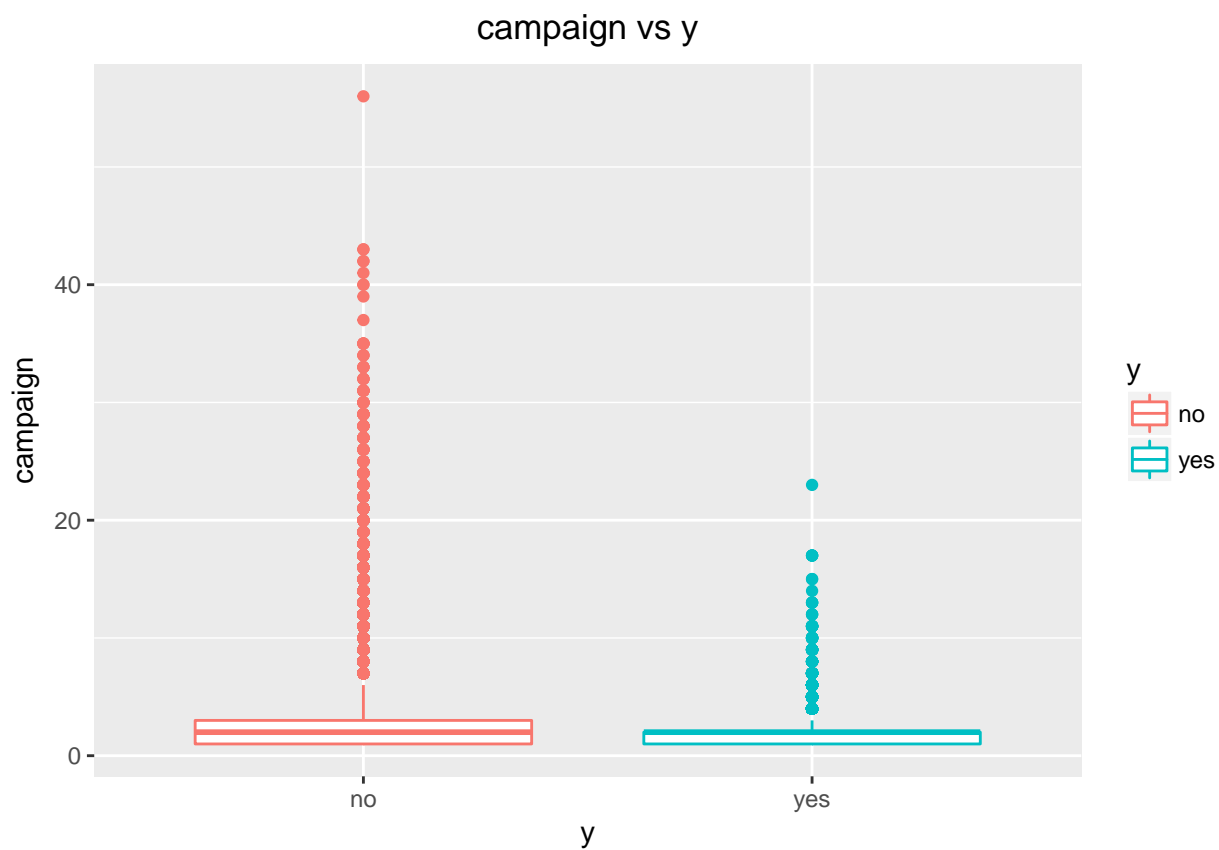


*# The boxplot of call duration and whether the customer took the subscription clearly
indicates that people who took subscription spend significantly more amount of time
speaking to the representative. The variable duration can be highly useful while
predicting y. We can actually predict that y="no" whenever call duration is 0 which
means that if a customer didn't attend the call then he/she didn't subscribe. And the
variable duration should be left out while building a realistic predictive model, as we
only get to know call duration after speaking to the customer, but we would anyway
know if a person subscribed or not (y="yes" or "no") by the end of the call. So this
variable while building a true predictive model which will be used by the organization
in future*

```
ggplot(bank, aes(x=y, y=duration, col=y))+  
  geom_boxplot()+  
  ggtitle("duration vs y")+  
  theme(plot.title = element_text(hjust = 0.5))
```



```
# The proportion table of campaign(number of times client was contacted during this  
# campaign) shows that it is very unlikely that client will say "yes" after contacting  
# the client more than 15 times with a probability of 1.4%  
ggplot(bank, aes(x=y, y=campaign, col=y))+  
  geom_boxplot()+  
  ggtitle("campaign vs y")+  
  theme(plot.title = element_text(hjust = 0.5))
```



```
table(bank$campaign, bank$y)
```

```
##
##      no  yes
## 1 15342 2300
## 2  9359 1211
## 3  4767  574
## 4  2402  249
## 5  1479  120
## 6   904   75
## 7   591   38
## 8   383   17
## 9   266   17
## 10  213   12
## 11  165   12
## 12  122    3
## 13   88    4
## 14   68    1
## 15   49    2
## 16   51    0
## 17   54    4
## 18   33    0
## 19   26    0
## 20   30    0
## 21   24    0
## 22   17    0
## 23   15    1
## 24   15    0
## 25    8    0
## 26    8    0
```

```
## 27 11 0
## 28 8 0
## 29 10 0
## 30 7 0
## 31 7 0
## 32 4 0
## 33 4 0
## 34 3 0
## 35 5 0
## 37 1 0
## 39 1 0
## 40 2 0
## 41 1 0
## 42 2 0
## 43 2 0
## 56 1 0
```

```
prop.table(table(bank[bank$campaign>15, ]$y))
```

```
##
##      no      yes
## 0.98591549 0.01408451
```

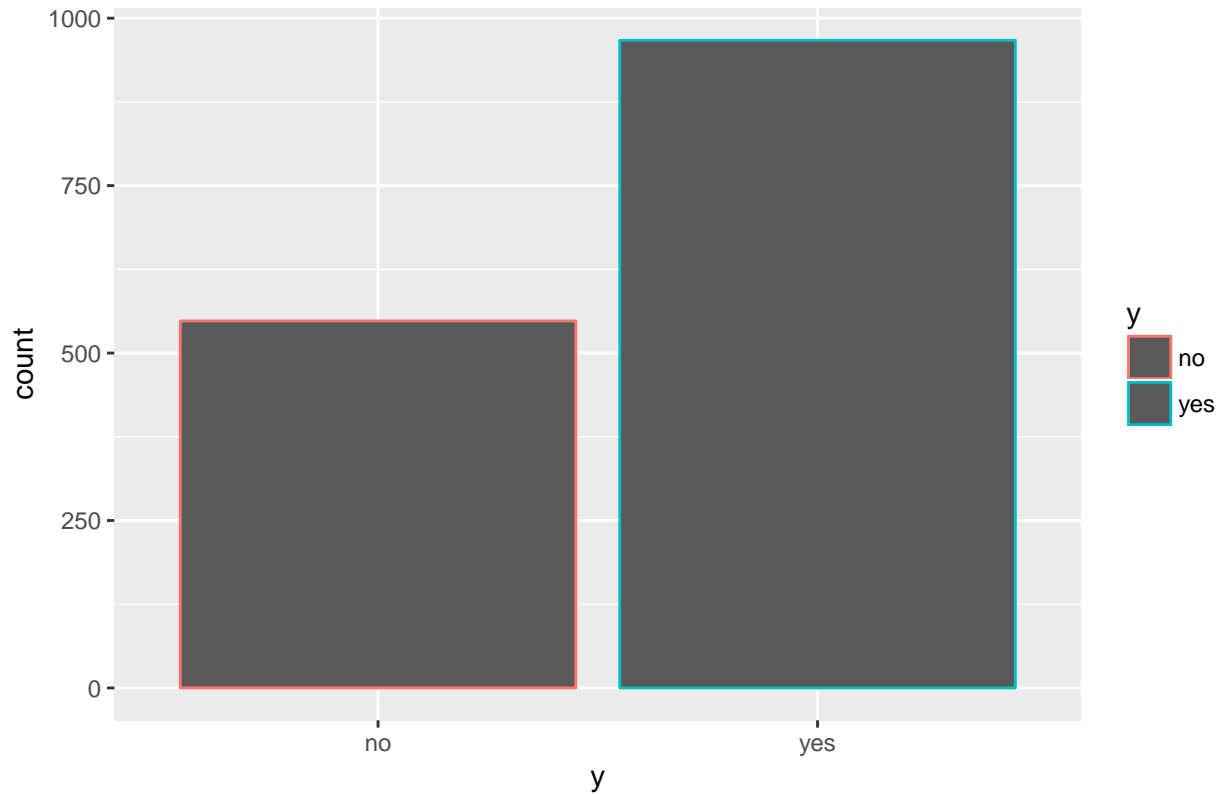
```
prop.table(table(bank[bank$campaign<15, ]$y))
```

```
##
##      no      yes
## 0.886396 0.113604
```

```
# The proportion table of pdays (number of days that passed by after the client was last
# contacted from a previous campaign. If a client was not contacted previously pdays will
# be 999) of people who were contacted previously and people who weren't shows that
# previously contacted clients have 63.8% chance of taking the subscription while people
# who weren't contacted previously only have 9% chance of taking the plan.
```

```
ggplot(bank[bank$pdays!=999,], aes(x=y, col=y))+
  geom_bar()+
  ggtitle("Histogram of y for people who were contacted after previous campaign")+
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people who were contacted after previous campaign

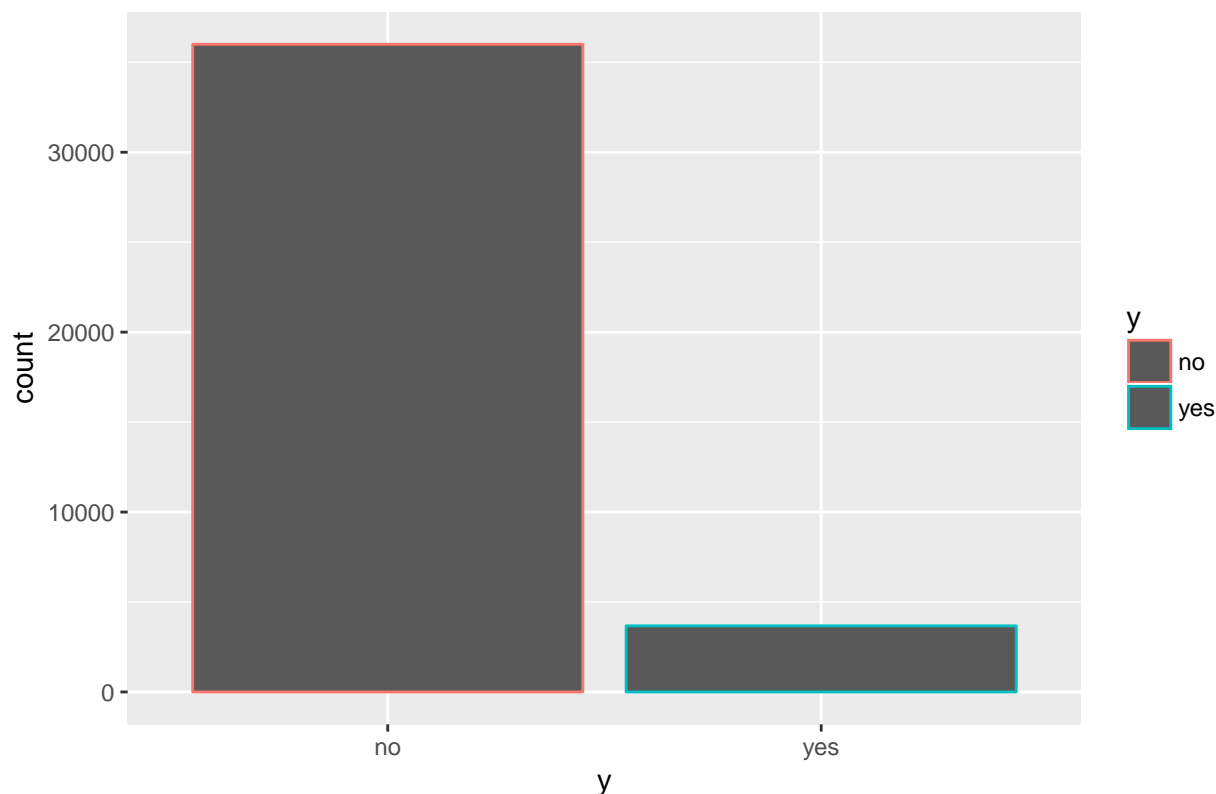


```
prop.table(table(bank[bank$pdays!=999,]$y))
```

```
##  
##      no      yes  
## 0.3617162 0.6382838
```

```
ggplot(bank[bank$pdays==999,], aes(x=y, col=y))+  
  geom_bar()+  
  ggtitle("Histogram of y for people who were not contacted after previous campaign")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people who were not contacted after previous campaign



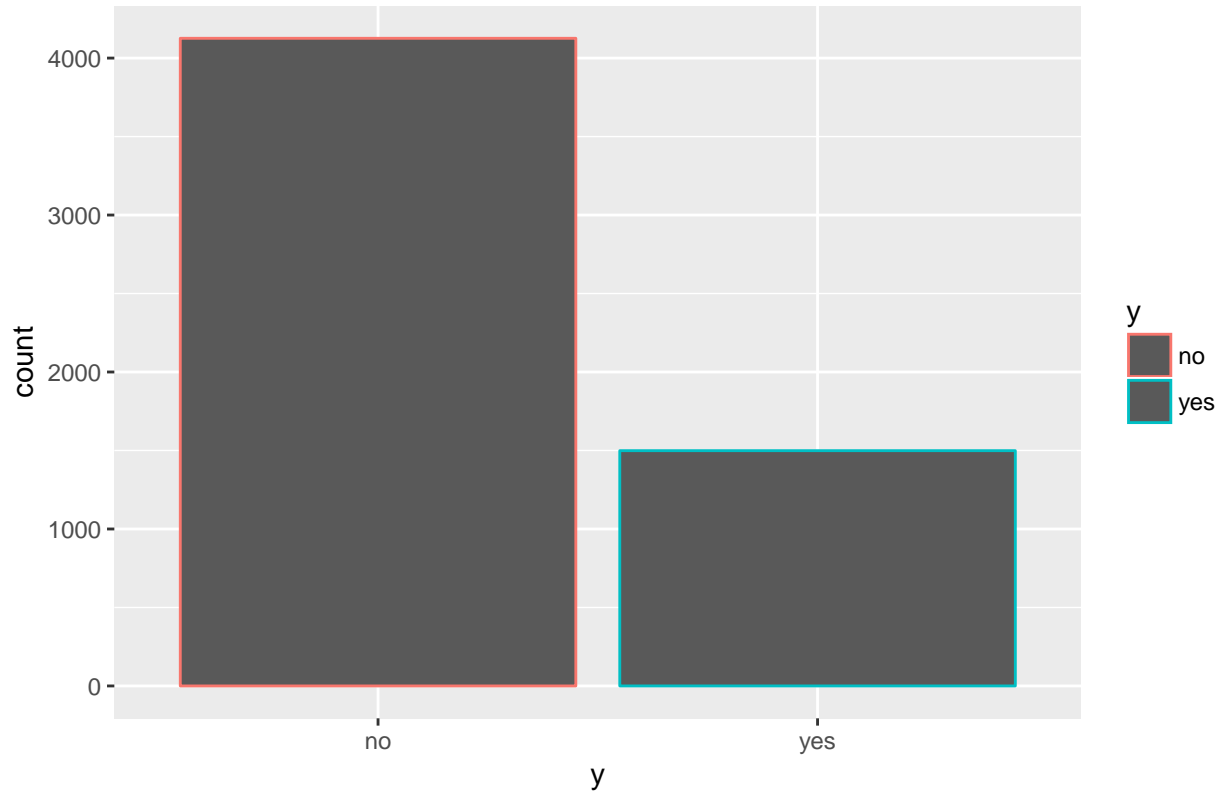
```
prop.table(table(bank[bank$pdays==999,]$y))
```

```
##
##          no          yes
## 0.90741814 0.09258186
```

The previous variable (number of contacts performed before this campaign and for this client) is very similar to campaign variable, and indicates that people who were contacted previously have higher chance of taking the subscription compared to the people who were not contacted before this campaign. By examining the relationship between pdays and previous using subsets of population, it is evident that, of those people who were contacted at least once during this campaign were all contacted at least once before this campaign. And complementarily, the people who were not contacted even once before this campaign are also not contacted even once in this campaign. This indicates that the variable previous is highly dependent on the variable pdays and doesn't play significant role in giving extra information

```
ggplot(bank[bank$previous!=0,], aes(x=y, col=y))+
  geom_bar()+
  ggtitle("Histogram of y for people who were conatacted before this campaign")+
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people who were conatacted before this campaign

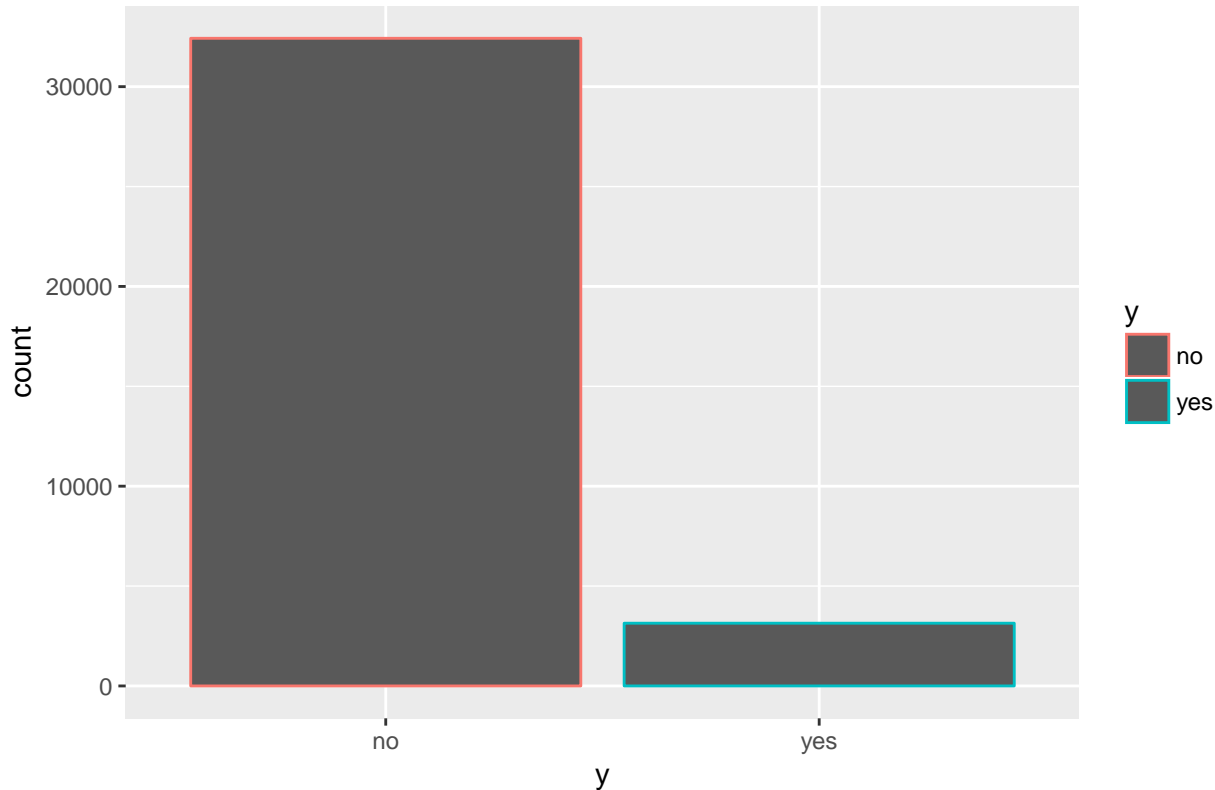


```
prop.table(table(bank[bank$previous!=0,]$y))
```

```
##  
##      no      yes  
## 0.7335111 0.2664889
```

```
ggplot(bank[bank$previous==0,], aes(x=y, col=y))+  
  geom_bar()+  
  ggtitle("Histogram of y for people who were not conatacted before this campaign")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people who were not conatacted before this campaign



```
prop.table(table(bank[bank$previous==0,]$y))
```

```
##
##      no      yes
## 0.91167787 0.08832213
```

```
table(bank[bank$pdays!=999,]$previous)
```

```
##
##  1  2  3  4  5  6  7
## 865 405 166 58 16  4  1
```

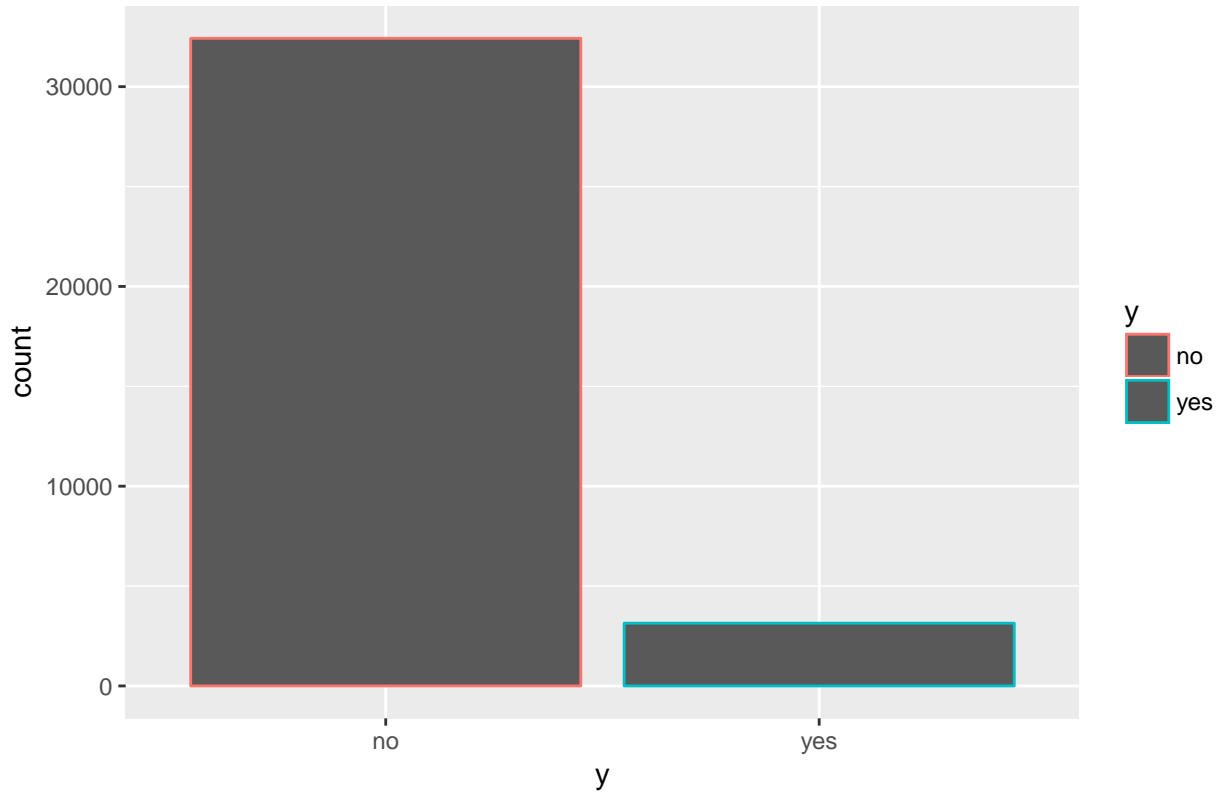
```
table(bank[bank$previous==0,]$pdays)
```

```
##
##    999
## 35563
```

Bar plots of each category of the variable poutcome(outcome of the previous marketing campaign) indicates that people whose outcome of the previous campaign is a success # have very high probability of taking the plan followed by people who rejected the offer # in previous campaign. The people who were not contacted previously at all have very low # chance of taking the plan.

```
ggplot(bank[bank$poutcome=="nonexistent",], aes(x=y, col=y))+
  geom_bar()+
  ggtitle("Histogram of y for people in nonexistent category")+
  theme(plot.title = element_text(hjust = 0.5))
```


Histogram of y for people in nonexistent category

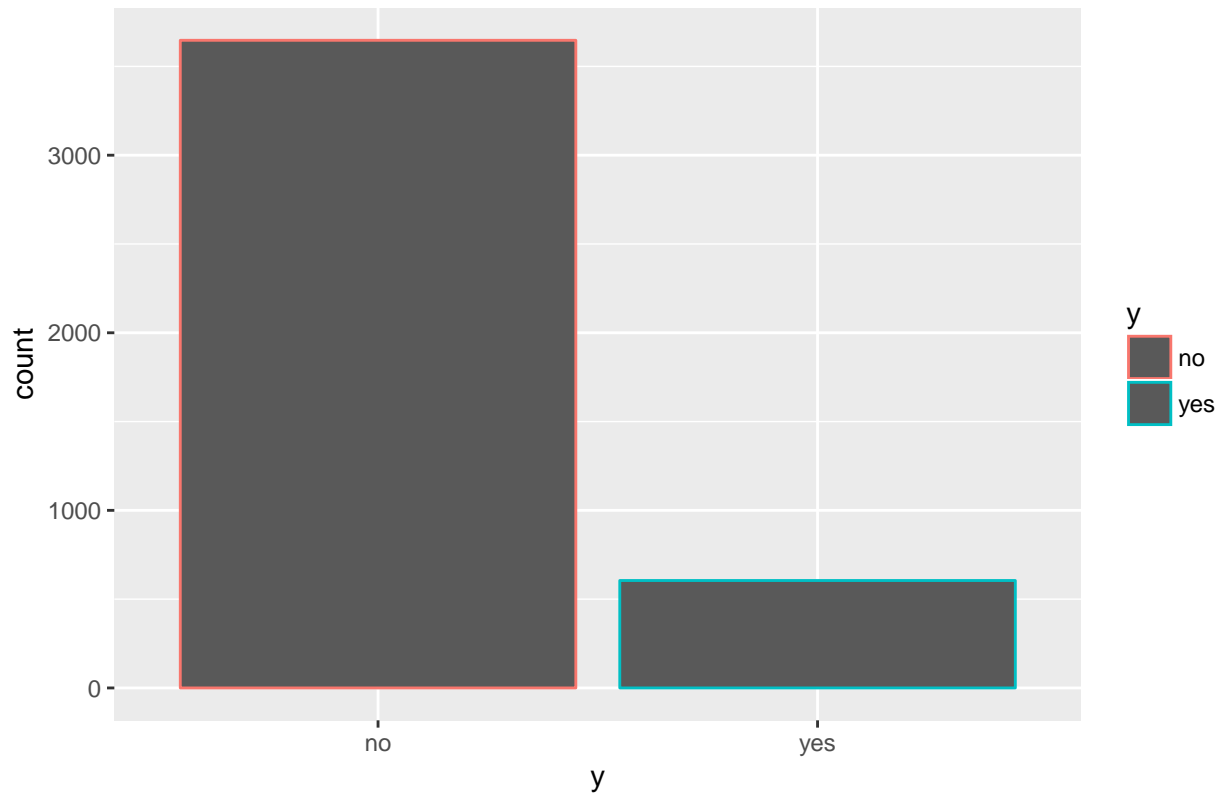


```
prop.table(table(bank[bank$poutcome=="nonexistent"],$y))
```

```
##  
##      no      yes  
## 0.91167787 0.08832213
```

```
ggplot(bank[bank$poutcome=="failure",], aes(x=y, col=y))+  
  geom_bar()+  
  ggtitle("Histogram of y for people in failure category")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people in failure category

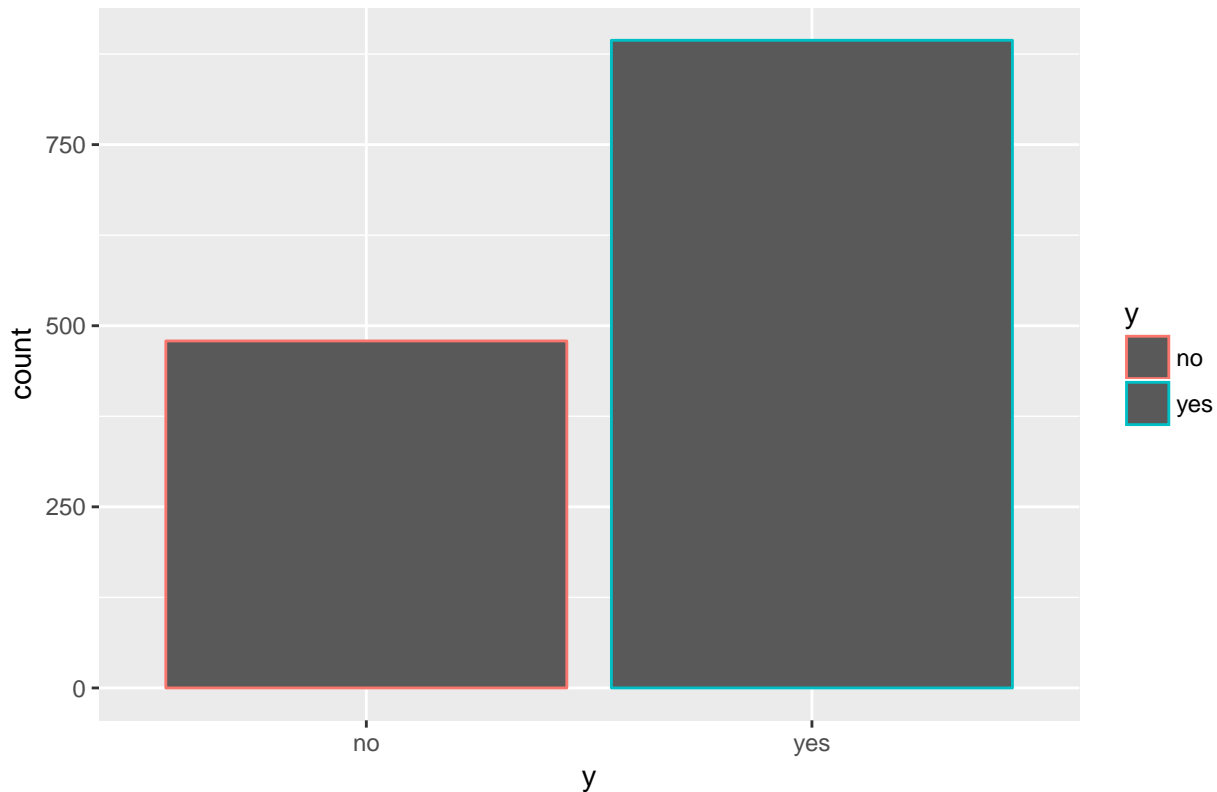


```
prop.table(table(bank[bank$poutcome=="failure",]$y))
```

```
##  
##      no      yes  
## 0.857714 0.142286
```

```
ggplot(bank[bank$poutcome=="success",], aes(x=y, col=y))+  
  geom_bar()+  
  ggtitle("Histogram of y for people in success category")+  
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of y for people in success category



```
prop.table(table(bank[bank$poutcome=="success",]$y))
```

```
##
##      no      yes
## 0.3488711 0.6511289
```

It is interesting to note that people who were non-existent in poutcome are the same people with pdays=999

```
table(bank[bank$poutcome=="nonexistent",]$y)
```

```
##
##      no      yes
## 32422  3141
```

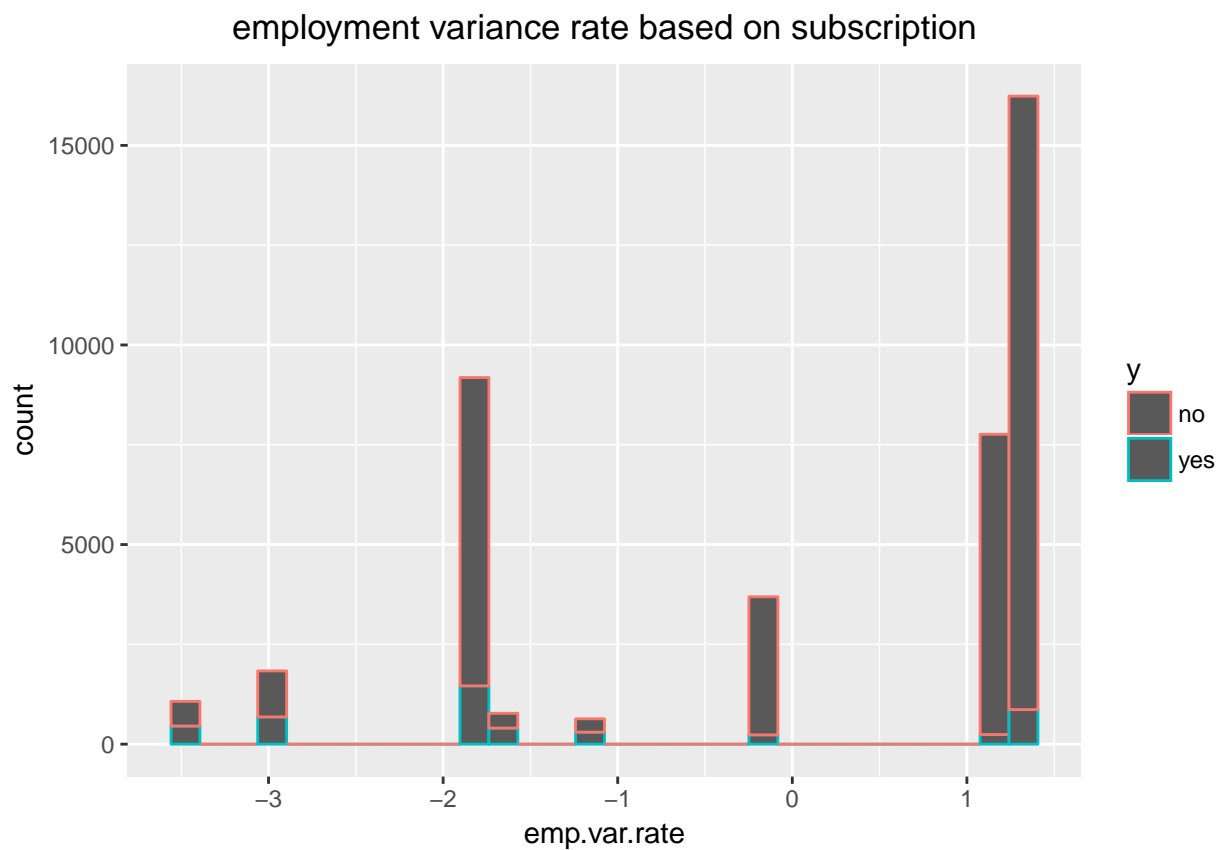
```
table(bank[bank$poutcome=="nonexistent"&bank$pdays==999,]$y)
```

```
##
##      no      yes
## 32422  3141
```

The probability taking the subscription significantly increases when employment variance rate is less than -1.

```
ggplot(data=bank, aes(x=emp.var.rate, col=y))+
  geom_histogram()+
  ggtitle("employment variance rate based on subscription")+
  theme(plot.title = element_text(hjust = 0.5))
```

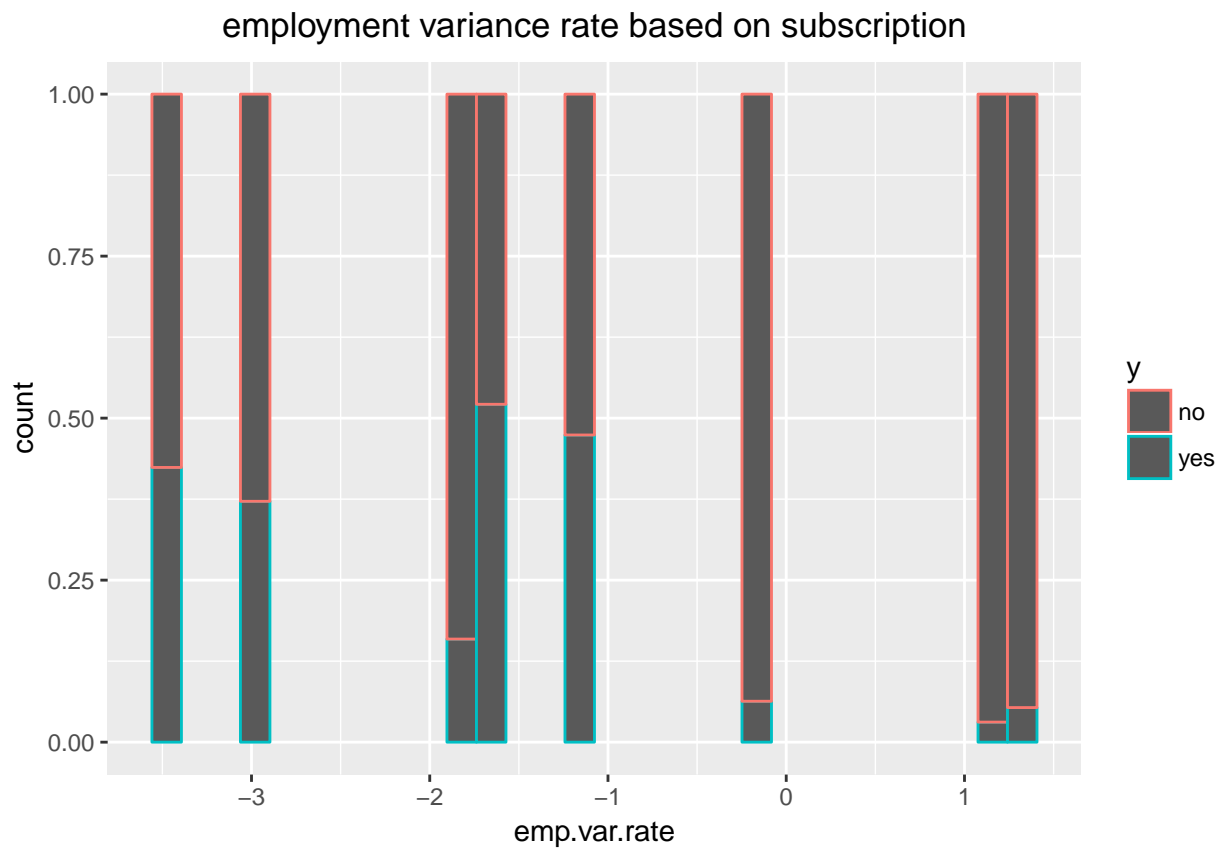
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
ggplot(data=bank, aes(x=emp.var.rate, col=y))+  
  geom_histogram(position = "fill")+  
  ggtitle("employment variance rate based on subscription")+  
  theme(plot.title = element_text(hjust = 0.5))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Warning: Removed 44 rows containing missing values (geom_bar).



*# A histogram of proportions of the variable consumer price index shows that the
concentration of people taking the plan is evenly spread on both higher and lower
sides of cpi, so we can't really make any generalizations about a particular group
being more favourable for saying "yes"*

```
ggplot(data=bank, aes(x=cons.price.idx, col=y))+
  geom_histogram(position = "fill")+
  ggtitle("consumer price index based on subscription")+
  theme(plot.title = element_text(hjust = 0.5))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

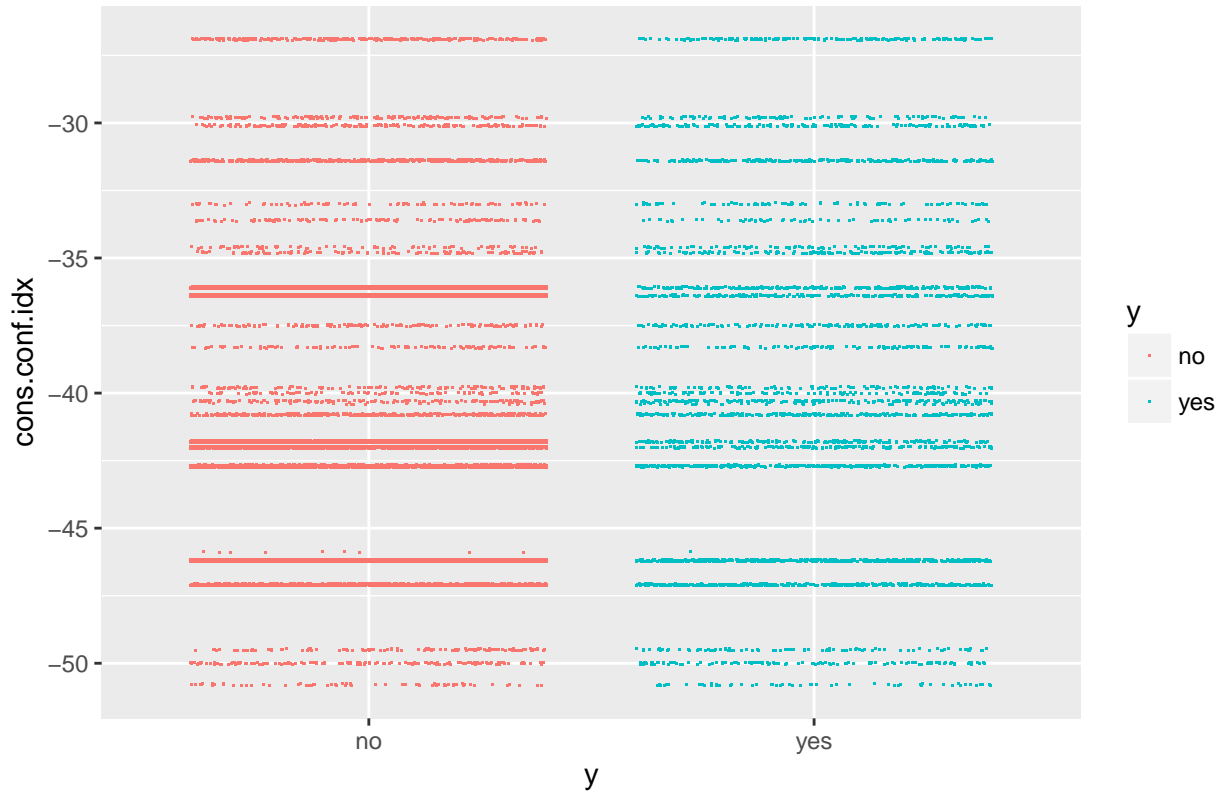
Warning: Removed 20 rows containing missing values (geom_bar).



*# The scatterplot and histogram of consumer confidence index indicates that the amount of
people who are taking the subscription mostly depends on the amount of people present in
that particular range of values and not actually on the consumer confidence index itself*

```
ggplot(data=bank, aes(x=y, y=cons.conf.idx, col=y))+
  geom_jitter(shape=46)+
  ggtitle("Consumer confidence index vs y")+
  theme(plot.title = element_text(hjust = 0.5))
```

Consumer confidence index vs y

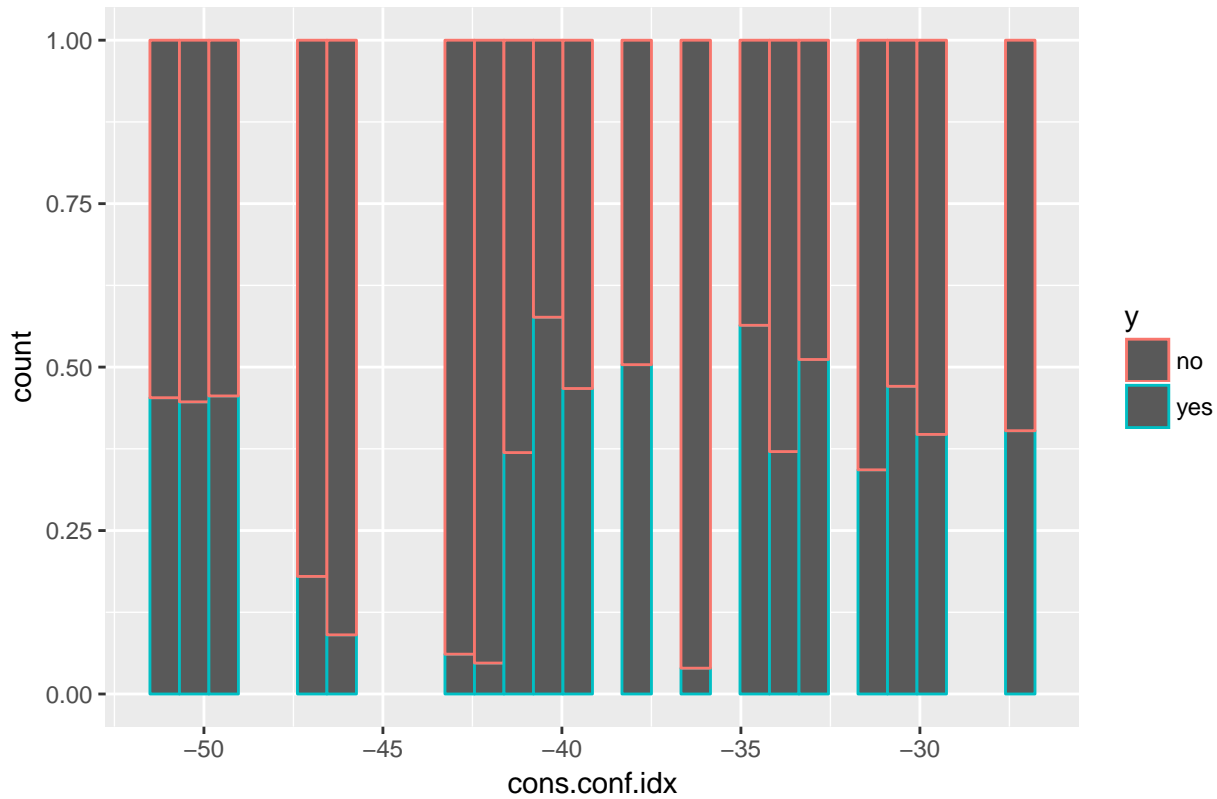


```
ggplot(data=bank, aes(x=cons.conf.idx, col=y))+
  geom_histogram(position = "fill")+
  ggtitle("Consumer confidence index based on subscription")+
  theme(plot.title = element_text(hjust = 0.5))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Warning: Removed 22 rows containing missing values (geom_bar).

Consumer confidence index based on subscription

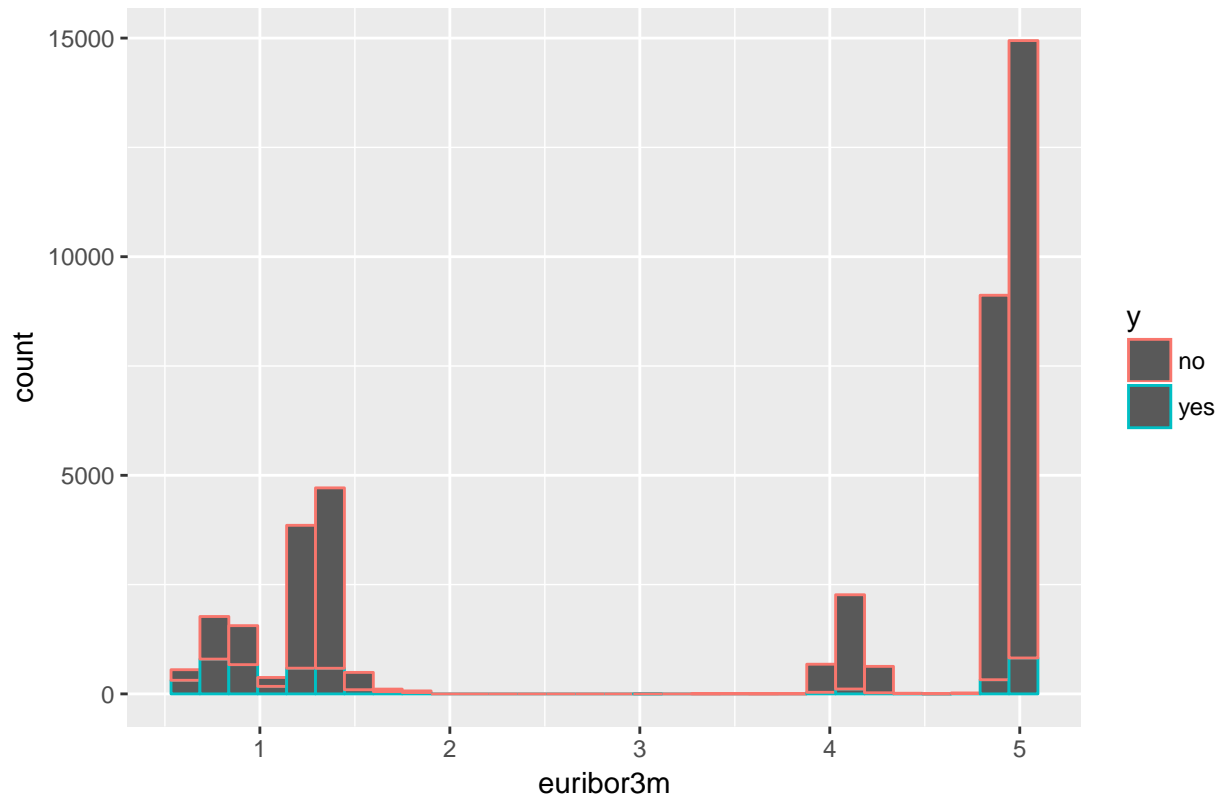


*# The histograms and proportion tables of euribor(Euro Interbank Offered Rate) shows that,
as euribor decreases the probability of people taking the plan increases significantly.
And when euribor drops below 1, there is very high chance of people taking the
subscription.*

```
ggplot(data=bank, aes(x=euribor3m, col=y))+  
  geom_histogram()+  
  ggtitle("Histogram of euribor rate based on subscription")+  
  theme(plot.title = element_text(hjust = 0.5))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Histogram of euribor rate based on subscription

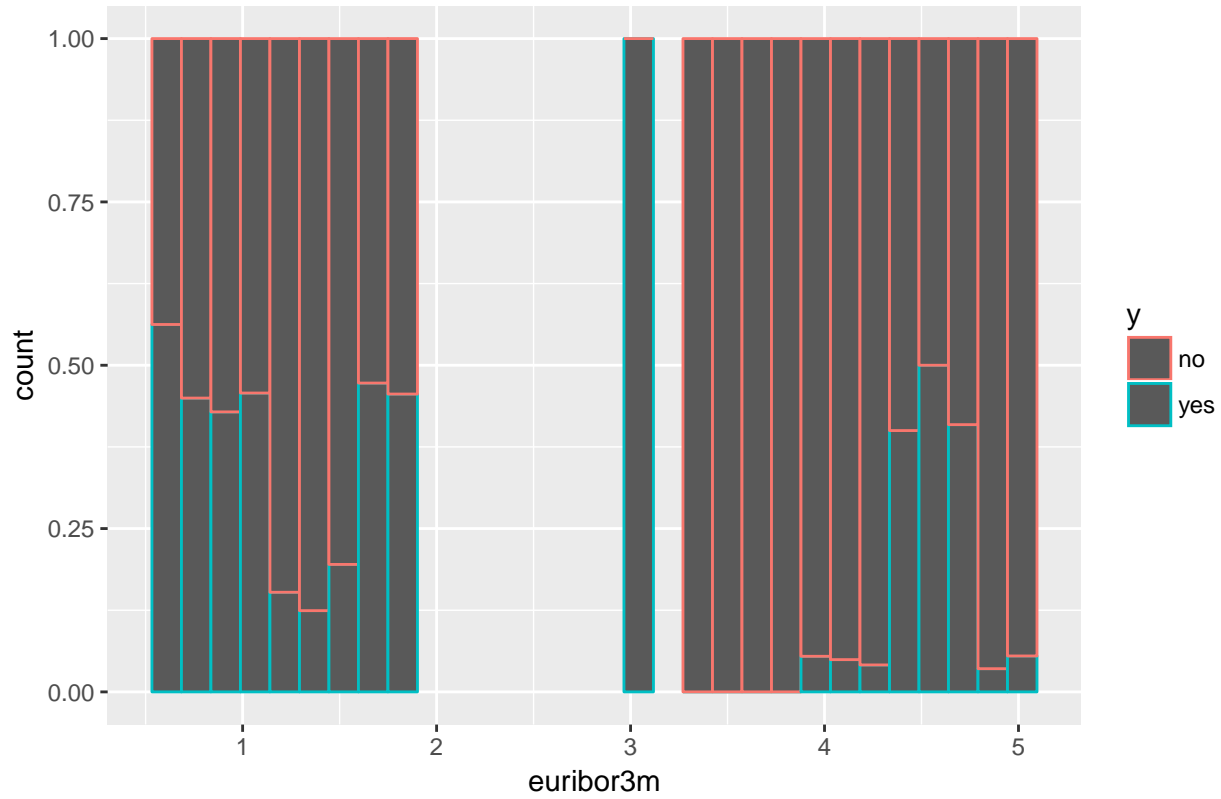


```
ggplot(data=bank, aes(x=euribor3m, col=y))+  
  geom_histogram(position = "fill") +  
  ggtitle("Histogram of euribor rate based on subscription") +  
  theme(plot.title = element_text(hjust = 0.5))
```

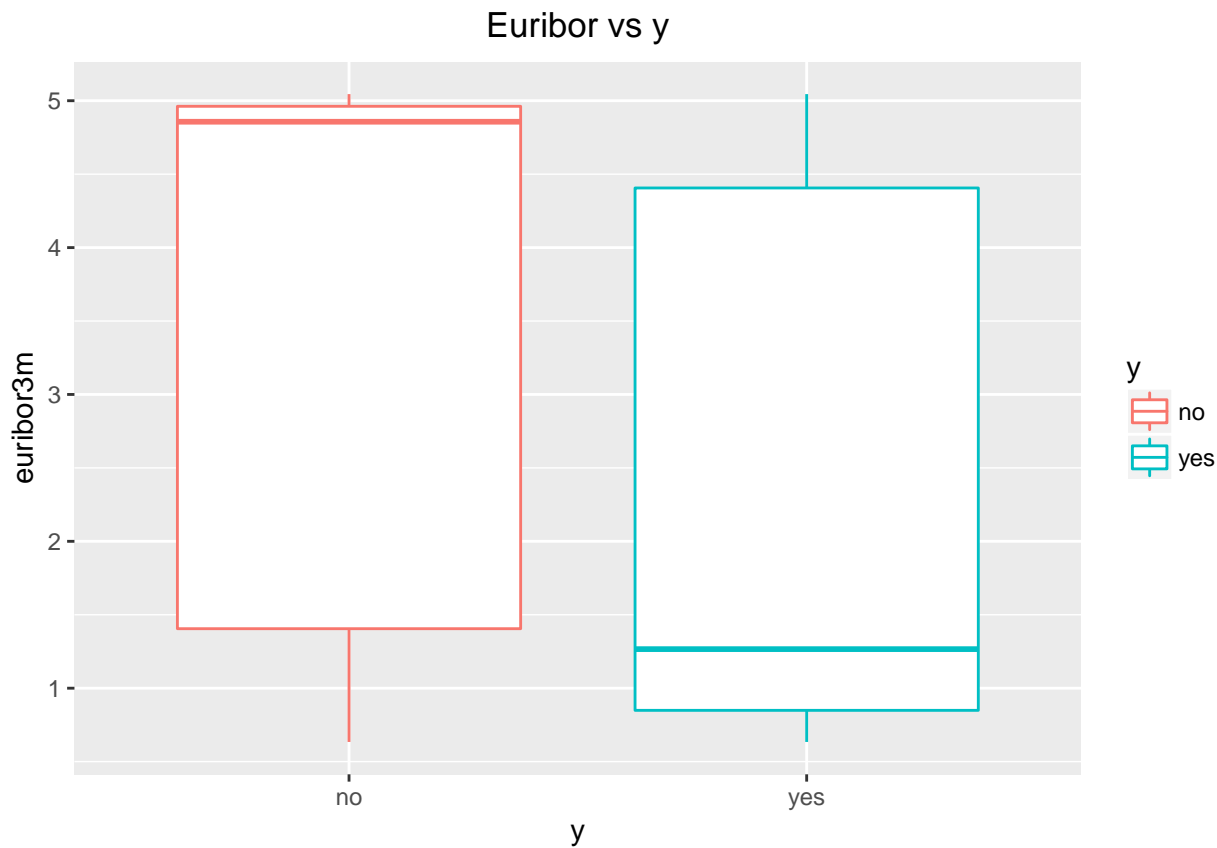
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Warning: Removed 16 rows containing missing values (geom_bar).

Histogram of euribor rate based on subscription



```
ggplot(bank, aes(x=y, y=euribor3m, col=y))+  
  geom_boxplot()+  
  ggtitle("Euribor vs y")+  
  theme(plot.title = element_text(hjust = 0.5))
```



```
prop.table(table(bank[bank$euribor3m<5,]$y))
```

```
##
##      no      yes
## 0.8874964 0.1125036
```

```
prop.table(table(bank[bank$euribor3m<3,]$y))
```

```
##
##      no      yes
## 0.7554453 0.2445547
```

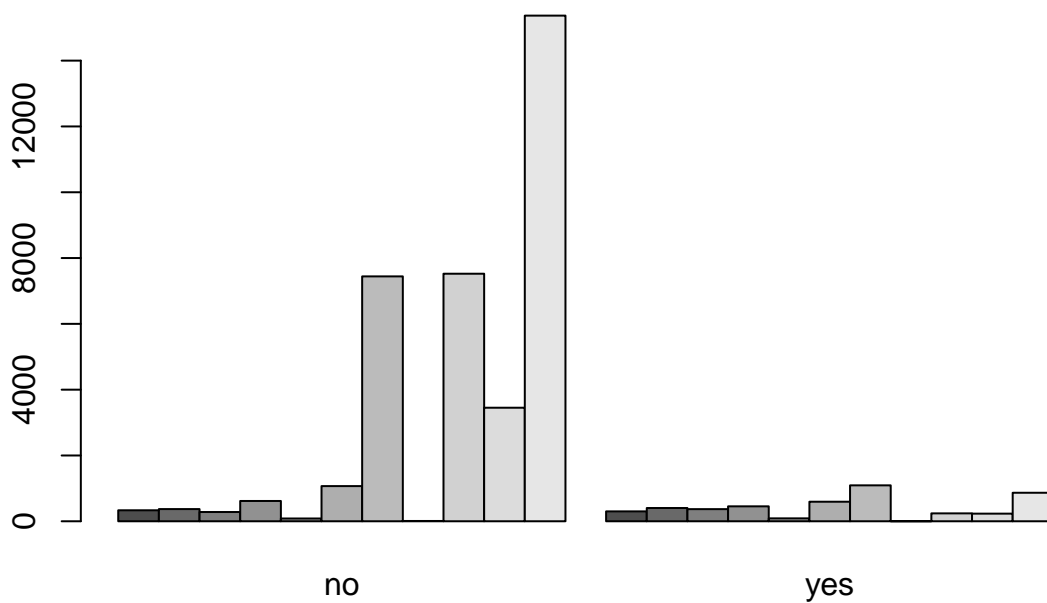
```
prop.table(table(bank[bank$euribor3m<1,]$y))
```

```
##
##      no      yes
## 0.5429306 0.4570694
```

*# The barplot, histogram and proportion tables of the nr.employed shows that, as the
number of employees increases the efficiency of the campaign decreases. When the number
of employees are less than 5000 the probability of a client accepting the offer
increases significantly.*

```
bartable <- table(bank$nr.employed, bank$y)
barplot(bartable, beside = TRUE, legend = levels(unique(bank$nr.employed)),
        main="employed vs y")
```

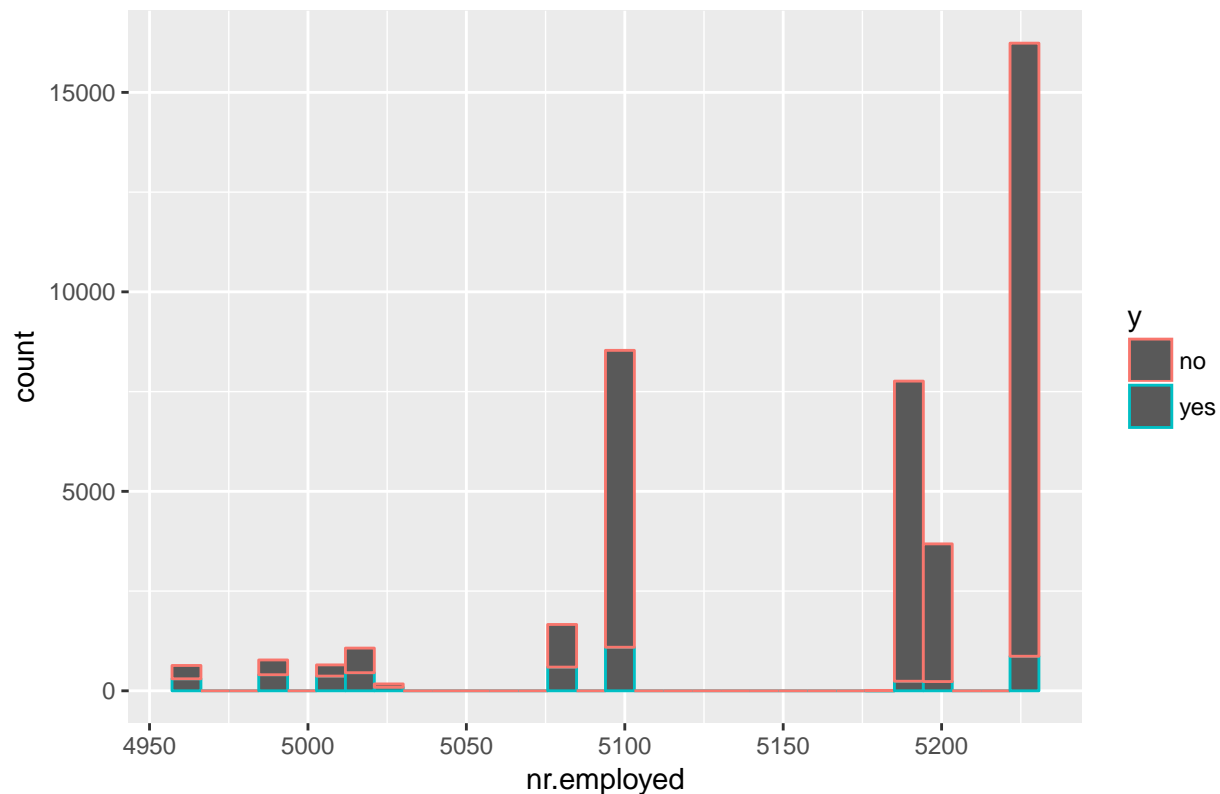
employed vs y



```
ggplot(data=bank, aes(x=nr.employed, col=y))+
  geom_histogram()+
  ggtitle("Histogram of nr.employed in relation with subscription")+
  theme(plot.title = element_text(hjust = 0.5))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Histogram of nr.employed in relation with subscription

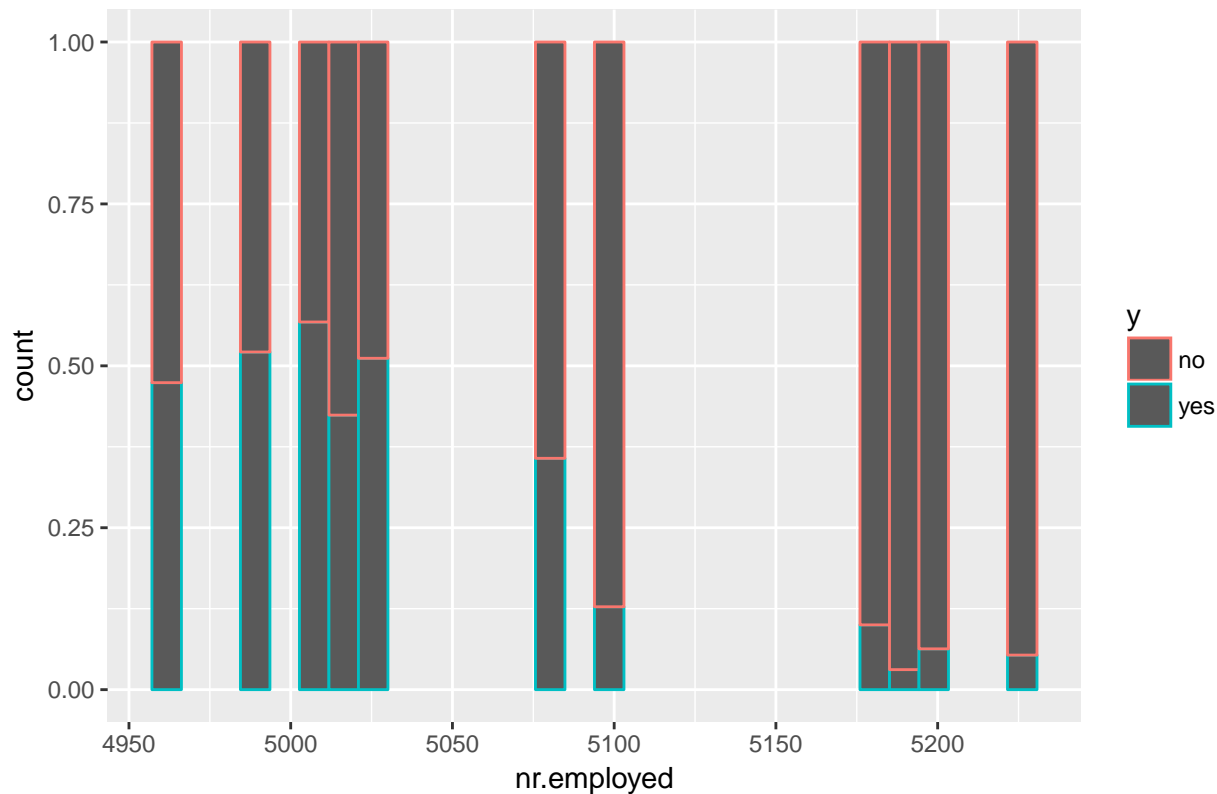


```
ggplot(data=bank, aes(x=nr.employed, col=y))+
  geom_histogram(position="fill")+
  ggtitle("Histogram of nr.employed in relation with subscription")+
  theme(plot.title = element_text(hjust = 0.5))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 38 rows containing missing values (geom_bar).
```

Histogram of nr.employed in relation with subscription



```
prop.table(table(bank[bank$nr.employed<5228,]$y))
```

```
##
##      no      yes
## 0.8487617 0.1512383
```

```
prop.table(table(bank[bank$nr.employed<5100,]$y))
```

```
##
##      no      yes
## 0.7554453 0.2445547
```

```
prop.table(table(bank[bank$nr.employed<5000,]$y))
```

```
##
## no yes
## 0.5 0.5
```

```
# Getting the indexes of factor columns from bank data set, to convert them into
# numeric for creating a correlation plot
```

```
bank_dup <- bank
factors_index <- which(sapply(bank_dup, is.factor))
factors_index
```

```
##      job      marital  education  default  housing      loan
##      2         3         4         5         6         7
##  contact      month day_of_week  poutcome      y
##      8         9         10        15        21
```

```
# Converting factor columns to numeric
```

```
bank_dup[,factors_index] <- lapply(factors_index, function(fac)
  {as.numeric(bank_dup[,fac])})
str(bank_dup)
```

```
## 'data.frame':    41188 obs. of  21 variables:
## $ age           : int  56 57 37 40 56 45 59 41 24 25 ...
## $ job           : num  4 8 8 1 8 8 1 2 10 8 ...
## $ marital       : num  2 2 2 2 2 2 2 2 3 3 ...
## $ education     : num  1 4 4 2 4 3 6 8 6 4 ...
## $ default       : num  1 2 1 1 1 2 1 2 1 1 ...
## $ housing       : num  1 1 3 1 1 1 1 1 3 3 ...
## $ loan          : num  1 1 1 1 3 1 1 1 1 1 ...
## $ contact       : num  2 2 2 2 2 2 2 2 2 2 ...
## $ month         : num  7 7 7 7 7 7 7 7 7 7 ...
## $ day_of_week   : num  2 2 2 2 2 2 2 2 2 2 ...
## $ duration      : int  261 149 226 151 307 198 139 217 380 50 ...
## $ campaign      : int  1 1 1 1 1 1 1 1 1 1 ...
## $ pdays         : int  999 999 999 999 999 999 999 999 999 999 ...
## $ previous      : int  0 0 0 0 0 0 0 0 0 0 ...
## $ poutcome      : num  2 2 2 2 2 2 2 2 2 2 ...
## $ emp.var.rate  : num  1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 ...
## $ cons.price.idx: num  94 94 94 94 94 ...
## $ cons.conf.idx : num  -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 ...
## $ euribor3m     : num  4.86 4.86 4.86 4.86 4.86 ...
## $ nr.employed   : num  5191 5191 5191 5191 5191 ...
## $ y             : num  1 1 1 1 1 1 1 1 1 1 ...
```

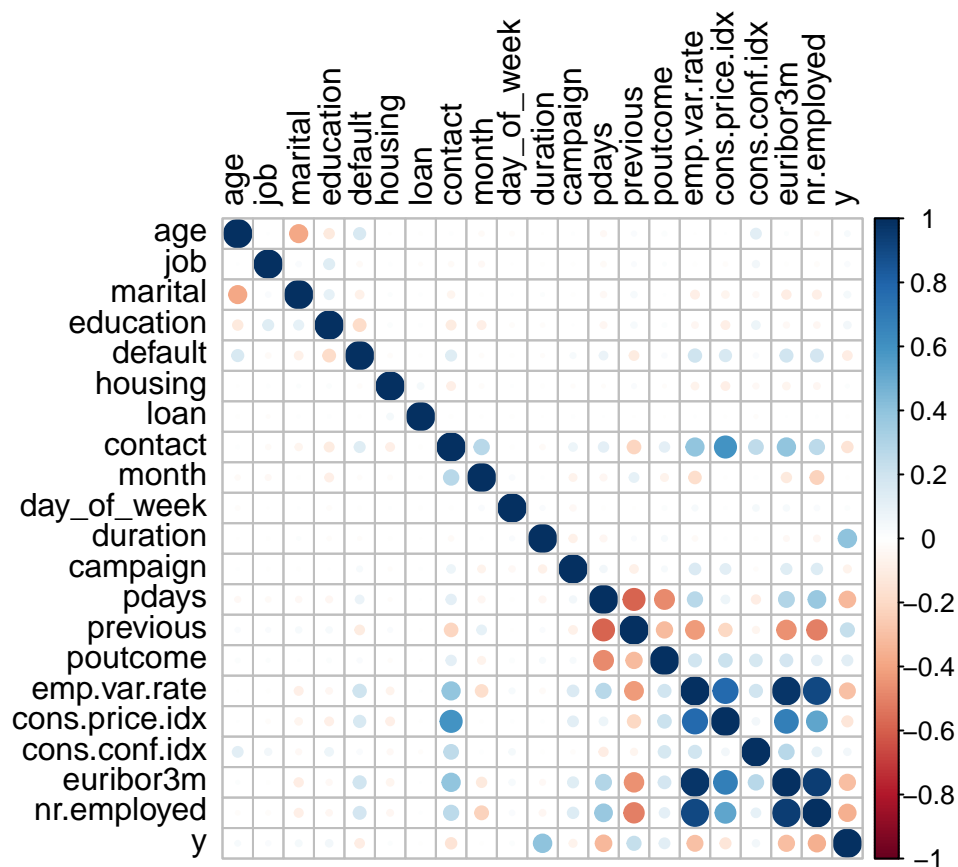
```
# Correlation plot of bank explains the correlation between different columns of bank
```

```
library(corrplot)
```

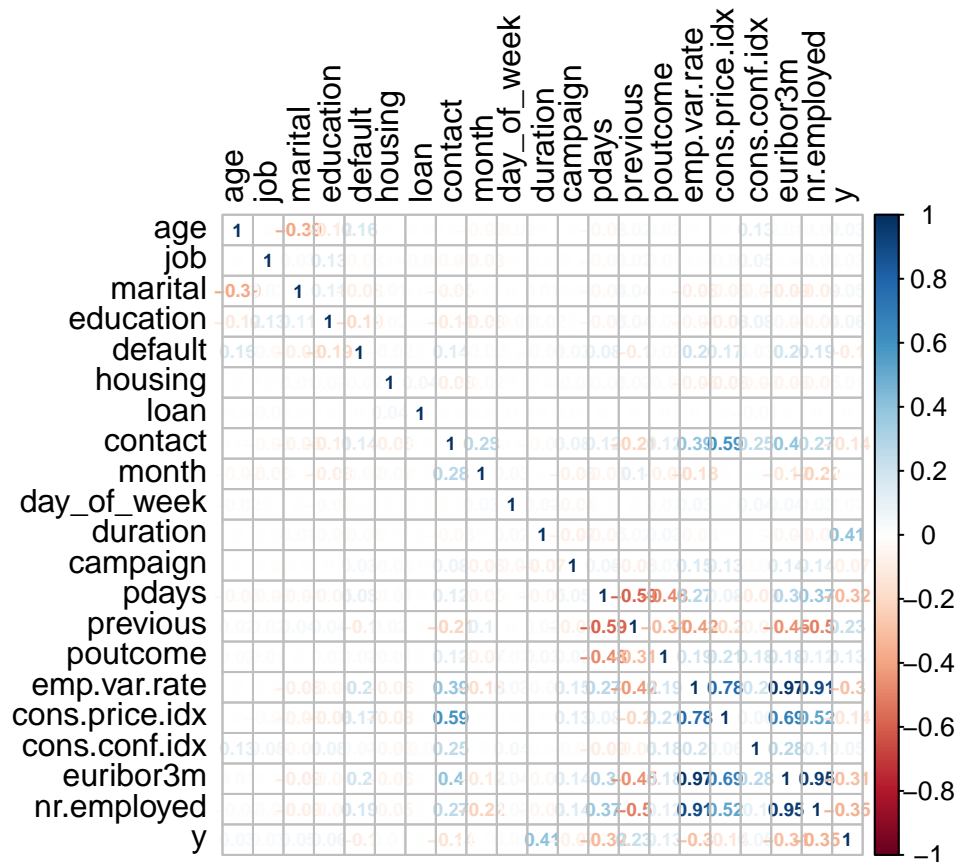
```
## Warning: package 'corrplot' was built under R version 3.4.2
```

```
## corrplot 0.84 loaded
```

```
C <- cor(bank_dup)
corrplot(C, tl.col="black")
```



```
corrplot(C, method = "number", number.cex=0.6, tl.col="black")
```



```
### Model building and evaluation ###
```

```
# Normalizing the numeric features in bank to reduce the bias towards features with  
# comparatively high numeric values
```

```
normalize <- function(x) {  
  return((x - min(x)) / (max(x) - min(x)))  
}  
factors_index <- which(sapply(bank, is.factor))  
factors_index
```

```
##      job      marital      education      default      housing      loan  
##      2        3          4            5            6            7  
##  contact      month day_of_week  poutcome            y  
##      8        9          10          15            21
```

```
bank_n <- as.data.frame(lapply(bank[, -factors_index], normalize))  
names(bank_n)
```

```
## [1] "age"           "duration"       "campaign"       "pdays"  
## [5] "previous"       "emp.var.rate"   "cons.price.idx" "cons.conf.idx"  
## [9] "euribor3m"      "nr.employed"
```

```
bank[names(bank_n)] <- bank_n[names(bank_n)]  
str(bank)
```

```
## 'data.frame':    41188 obs. of  21 variables:  
## $ age           : num  0.481 0.494 0.247 0.284 0.481 ...  
## $ job           : Factor w/ 12 levels "admin.", "blue-collar", ...: 4 8 8 1 8 8 1 2 10 8 ...  
## $ marital       : Factor w/ 4 levels "divorced", "married", ...: 2 2 2 2 2 2 2 3 3 ...  
## $ education     : Factor w/ 8 levels "basic.4y", "basic.6y", ...: 1 4 4 2 4 3 6 8 6 4 ...  
## $ default       : Factor w/ 3 levels "no", "unknown", ...: 1 2 1 1 1 2 1 2 1 1 ...  
## $ housing       : Factor w/ 3 levels "no", "unknown", ...: 1 1 3 1 1 1 1 1 3 3 ...  
## $ loan          : Factor w/ 3 levels "no", "unknown", ...: 1 1 1 1 3 1 1 1 1 1 ...  
## $ contact       : Factor w/ 2 levels "cellular", "telephone": 2 2 2 2 2 2 2 2 2 2 ...  
## $ month         : Factor w/ 10 levels "apr", "aug", "dec", ...: 7 7 7 7 7 7 7 7 7 7 ...  
## $ day_of_week   : Factor w/ 5 levels "fri", "mon", "thu", ...: 2 2 2 2 2 2 2 2 2 2 ...  
## $ duration      : num  0.0531 0.0303 0.046 0.0307 0.0624 ...  
## $ campaign      : num  0 0 0 0 0 0 0 0 0 0 ...  
## $ pdays         : num  1 1 1 1 1 1 1 1 1 1 ...  
## $ previous      : num  0 0 0 0 0 0 0 0 0 0 ...  
## $ poutcome      : Factor w/ 3 levels "failure", "nonexistent", ...: 2 2 2 2 2 2 2 2 2 2 ...  
## $ emp.var.rate  : num  0.938 0.938 0.938 0.938 0.938 ...  
## $ cons.price.idx: num  0.699 0.699 0.699 0.699 0.699 ...  
## $ cons.conf.idx : num  0.603 0.603 0.603 0.603 0.603 ...  
## $ euribor3m     : num  0.957 0.957 0.957 0.957 0.957 ...  
## $ nr.employed   : num  0.86 0.86 0.86 0.86 0.86 ...  
## $ y            : Factor w/ 2 levels "no", "yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
# Splitting the bank data set into training and testing sets  
library(irr)
```

```
## Loading required package: lpSolve  
library(ROCR)
```

```
## Loading required package: gplots  
##  
## Attaching package: 'gplots'
```



```

## The following object is masked from 'package:stats':
##
##      lowess
library(caret)

## Loading required package: lattice
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'zone/tz/2017c.
## 1.0/zoneinfo/America/New_York'
library(gmodels)
set.seed(141)
train_ind <- createDataPartition(bank$y, p=0.75, list=FALSE)
train_data <- bank[train_ind, ]
test_data <- bank[-train_ind, ]

# The target variable y is uniformly distributed among both train and test sets
prop.table(table(train_data$y))

##
##      no      yes
## 0.8873458 0.1126542
prop.table(table(test_data$y))

##
##      no      yes
## 0.8873458 0.1126542
### Naive Bayes ###
library(e1071)

set.seed(141)
# Building naive bayes model using train data
bayes_model <- naiveBayes(train_data[-21], train_data$y, laplace = 3)
bayes_model

##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = train_data[-21], y = train_data$y, laplace = 3)
##
## A-priori probabilities:
## train_data$y
##      no      yes
## 0.8873458 0.1126542
##
## Conditional probabilities:
##      age
## train_data$y      [,1]      [,2]
##      no  0.2828580 0.1220641
##      yes 0.2955974 0.1711786
##
##      job
## train_data$y      admin. blue-collar entrepreneur housemaid management
##      no  0.247458739 0.236528582  0.035996648 0.026159507 0.071483222
##      yes 0.282992036 0.130546075  0.027303754 0.024744027 0.074800910

```

```

##          job
## train_data$y    retired self-employed    services    student    technician
##          no 0.034903632 0.034757897 0.098917915 0.017196779 0.163915911
##          yes 0.095847554 0.034129693 0.069681456 0.064846416 0.155858931
##          job
## train_data$y    unemployed    unknown
##          no 0.024301381 0.008379786
##          yes 0.030716724 0.008532423
##
##          marital
## train_data$y    divorced    married    single    unknown
##          no 0.112423878 0.613572549 0.271852095 0.002151479
##          yes 0.106529210 0.542096220 0.348224513 0.003150057
##
##          education
## train_data$y    basic.4y    basic.6y    basic.9y    high.school
##          no 0.1015855659 0.0575177693 0.1539639147 0.2306542737
##          yes 0.0924657534 0.0428082192 0.0970319635 0.2248858447
##          education
## train_data$y    illiterate    professional.course    university.degree
##          no 0.0005831966    0.1270275196    0.2877346455
##          yes 0.0019977169    0.1269977169    0.3567351598
##          education
## train_data$y    unknown
##          no 0.0409331146
##          yes 0.0570776256
##
##          default
## train_data$y    no    unknown    yes
##          no 0.7749452954 0.2248723559 0.0001823487
##          yes 0.9051304099 0.0940097449 0.0008598452
##
##          housing
## train_data$y    no    unknown    yes
##          no 0.4530999 0.0245806 0.5223195
##          yes 0.4396675 0.0246489 0.5356836
##
##          loan
## train_data$y    no    unknown    yes
##          no 0.8238512 0.0245806 0.1515682
##          yes 0.8314703 0.0246489 0.1438808
##
##          contact
## train_data$y    cellular    telephone
##          no 0.6074333 0.3925667
##          yes 0.8293173 0.1706827
##
##          month
## train_data$y    apr    aug    dec    jul    jun
##          no 0.057213658 0.149375023 0.002623811 0.176341970 0.131044787
##          yes 0.113105413 0.138746439 0.021652422 0.138461538 0.120797721
##          month
## train_data$y    mar    may    nov    oct    sep
##          no 0.007834991 0.354651798 0.100761634 0.011406290 0.008746037
##          yes 0.060968661 0.190313390 0.091737892 0.069515670 0.054700855
##

```

```
##          day_of_week
## train_data$y      fri      mon      thu      tue      wed
##          no 0.1911325 0.2076861 0.2077591 0.1970393 0.1963830
##          yes 0.1825465 0.1814020 0.2257511 0.2068670 0.2034335
##
##          duration
## train_data$y      [,1]      [,2]
##          no 0.04490545 0.04230937
##          yes 0.11229918 0.08267516
##
##          campaign
## train_data$y      [,1]      [,2]
##          no 0.02983606 0.05225394
##          yes 0.01907524 0.02972799
##
##          pdays
## train_data$y      [,1]      [,2]
##          no 0.9849543 0.1213524
##          yes 0.7940512 0.4029340
##
##          previous
## train_data$y      [,1]      [,2]
##          no 0.01886625 0.05824195
##          yes 0.07089491 0.12302136
##
##          poutcome
## train_data$y      failure nonexistent      success
##          no 0.09956236 0.88719912 0.01323851
##          yes 0.13470909 0.67526512 0.19002580
##
##          emp.var.rate
## train_data$y      [,1]      [,2]
##          no 0.7593705 0.3091820
##          yes 0.4522450 0.3401953
##
##          cons.price.idx
## train_data$y      [,1]      [,2]
##          no 0.5465981 0.2181408
##          yes 0.4503395 0.2640743
##
##          cons.conf.idx
## train_data$y      [,1]      [,2]
##          no 0.4269046 0.1840212
##          yes 0.4642536 0.2579954
##
##          euribor3m
## train_data$y      [,1]      [,2]
##          no 0.7193968 0.3717477
##          yes 0.3399032 0.3971505
##
##          nr.employed
## train_data$y      [,1]      [,2]
##          no 0.8029169 0.2441870
##          yes 0.4973375 0.3322022
```

```
# Applying the model on the test data to predict the dependent variable
bayes_pred <- predict(bayes_model, test_data[-21])
```

```
str(bayes_pred)
```

```
## Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
# The model has accuracy of around 86% which is good. The kappa value of 0.42 suggests  
# a moderate agreement between the true and predicted values
```

```
CrossTable(bayes_pred, test_data$y)
```

```
##  
##  
## Cell Contents  
## |-----|  
## | N |  
## | Chi-square contribution |  
## | N / Row Total |  
## | N / Col Total |  
## | N / Table Total |  
## |-----|  
##  
##  
## Total Observations in Table: 10297  
##  
##  
## | test_data$y  
## bayes_pred | no | yes | Row Total |  
## -----|-----|-----|-----|  
## no | 8177 | 444 | 8621 |  
## | 36.332 | 286.175 | |  
## | 0.948 | 0.052 | 0.837 |  
## | 0.895 | 0.383 | |  
## | 0.794 | 0.043 | |  
## -----|-----|-----|-----|  
## yes | 960 | 716 | 1676 |  
## | 186.883 | 1472.027 | |  
## | 0.573 | 0.427 | 0.163 |  
## | 0.105 | 0.617 | |  
## | 0.093 | 0.070 | |  
## -----|-----|-----|-----|  
## Column Total | 9137 | 1160 | 10297 |  
## | 0.887 | 0.113 | |  
## -----|-----|-----|-----|  
##  
##
```

```
confusionMatrix(bayes_pred, test_data$y, positive = "yes")
```

```
## Confusion Matrix and Statistics  
##  
## Reference  
## Prediction no yes  
## no 8177 444  
## yes 960 716  
##  
## Accuracy : 0.8636  
## 95% CI : (0.8569, 0.8702)  
## No Information Rate : 0.8873  
## P-Value [Acc > NIR] : 1  
##
```

```
##           Kappa : 0.4289
## McNemar's Test P-Value : <2e-16
##
##           Sensitivity : 0.61724
##           Specificity : 0.89493
##           Pos Pred Value : 0.42721
##           Neg Pred Value : 0.94850
##           Prevalence : 0.11265
##           Detection Rate : 0.06953
##           Detection Prevalence : 0.16277
##           Balanced Accuracy : 0.75609
##
##           'Positive' Class : yes
##
```

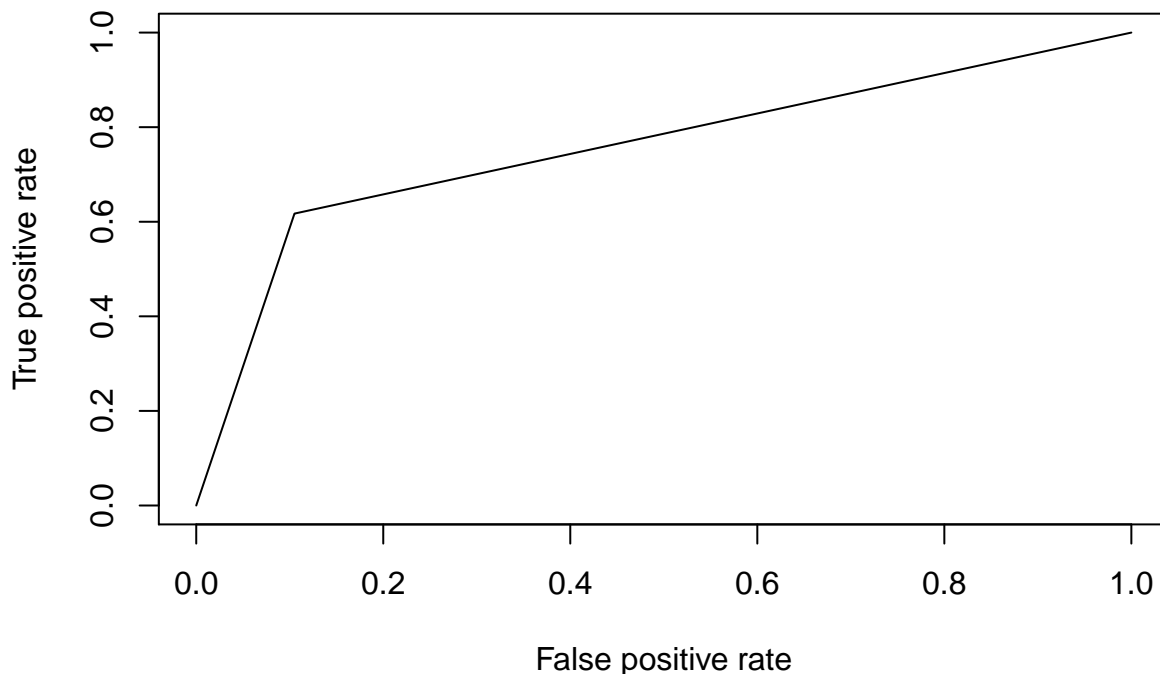
```
nb_accuracy <- confusionMatrix(bayes_pred,test_data$y, positive = "yes")$overall[[1]]
nb_accuracy <- nb_accuracy*100
nb_accuracy
```

```
## [1] 86.36496
```

*# Evaluation of the model using ROC curve and AUC(area under the curve) shows the model
is performing fine in predicting the false positives and false negatives with auc value
of 0.75, which has value of 1 for ideal case.*

```
pred_nb <- prediction(predictions = as.numeric(bayes_pred), labels = as.numeric(test_data$y))
perf_nb <- performance(pred_nb,measure = "tpr", x.measure = "fpr")
plot(perf_nb, main="Naive Bayes")
```

Naive Bayes



```
perf_auc_nb <- performance(pred_nb, measure = "auc")
nb_auc <- unlist(perf_auc_nb@y.values)
nb_auc
```

```
## [1] 0.756087
```

```

### Decision tree ###

library(C50)

set.seed(141)
# Building a decision tree classification model using training set data
decision_tree <- C5.0(train_data[-21], train_data$y, trails=20)
# The summary of decision tree model shows that the variables poutcome, duration,
# nr.employed, month, age and emp.var.rate are the most important variables in predicting
# the target variable y
summary(decision_tree)

##
## Call:
## C5.0.default(x = train_data[-21], y = train_data$y, trails = 20)
##
##
## C5.0 [Release 2.07 GPL Edition]          Sun Dec 10 17:34:15 2017
## -----
##
## Class specified by attribute `outcome'
##
## Read 30891 cases (21 attributes) from undefined.data
##
## Decision tree:
##
## poutcome = success:
## :...duration <= 0.03273689:
## :   :...cons.conf.idx <= 0.376569: no (69/3)
## :   :   cons.conf.idx > 0.376569:
## :   :     :...campaign > 0.01818182:
## :   :     :   :...marital = divorced: yes (3/1)
## :   :     :   :   marital in {married,single,unknown}: no (25/1)
## :   :     :   :   campaign <= 0.01818182:
## :   :     :   :     :...month in {jun,oct}: no (39/13)
## :   :     :   :     :   month = apr:
## :   :     :   :     :     :...housing in {no,unknown}: no (3)
## :   :     :   :     :     :   housing = yes: yes (1)
## :   :     :   :     :   month = dec:
## :   :     :   :     :     :...duration <= 0.02806019: no (3)
## :   :     :   :     :     :   duration > 0.02806019: yes (2)
## :   :     :   :     :   month = jul:
## :   :     :   :     :     :...duration <= 0.02704351: no (6)
## :   :     :   :     :     :   duration > 0.02704351: yes (2)
## :   :     :   :     :   month = mar:
## :   :     :   :     :     :...housing in {no,unknown}: yes (5)
## :   :     :   :     :     :   housing = yes: no (5/1)
## :   :     :   :     :   month = may:
## :   :     :   :     :     :...duration <= 0.02704351: no (3)
## :   :     :   :     :     :   duration > 0.02704351: yes (3)
## :   :     :   :     :   month = nov:
## :   :     :   :     :     :...euribor3m <= 0.01836318: yes (14/1)
## :   :     :   :     :     :   euribor3m > 0.01836318: no (2)
## :   :     :   :     :   month = sep:
## :   :     :   :     :     :...housing = no: yes (4)
## :   :     :   :     :     :   housing in {unknown,yes}: no (11/4)

```

```

## : : month = aug:
## : : ...age <= 0.3580247:
## : : ...euribor3m <= 0.04919519: yes (7/2)
## : : : euribor3m > 0.04919519: no (18/2)
## : : age > 0.3580247:
## : : ...housing in {no,unknown}: no (3)
## : : housing = yes: yes (14/6)
## : duration > 0.03273689:
## : ...nr.employed <= 0.4257089: yes (649/116)
## : nr.employed > 0.4257089:
## : ...month = mar: yes (2)
## : month in {aug,dec,jul,jun,nov,oct,sep}: no (15/2)
## : month = apr:
## : ...pdays <= 0.007007007: yes (30/7)
## : : pdays > 0.007007007: no (6/1)
## : month = may:
## : ...job in {entrepreneur,housemaid,management,retired,
## : : self-employed,student,unknown}: no (10)
## : job in {technician,unemployed}: yes (15/4)
## : job = admin.:
## : ...day_of_week in {fri,wed}: yes (6/1)
## : : day_of_week in {mon,tue}: no (7)
## : : day_of_week = thu:
## : : ...housing = no: yes (1)
## : : housing in {unknown,yes}: no (3)
## : job = services:
## : ...education in {basic.4y,basic.6y,basic.9y,illiterate,
## : : professional.course,unknown}: yes (3)
## : : education = university.degree: no (1)
## : : education = high.school:
## : : ...housing = no: yes (2)
## : : housing in {unknown,yes}: no (2)
## : job = blue-collar:
## : ...duration <= 0.09109394: no (15/1)
## : duration > 0.09109394:
## : ...education in {basic.4y,basic.6y,high.school,illiterate,
## : : professional.course,university.degree,
## : : unknown}: yes (5)
## : education = basic.9y:
## : ...day_of_week = thu: yes (2)
## : : day_of_week in {fri,mon,tue,wed}: no (4)
## poutcome in {failure,nonexistent}:
## ...duration <= 0.07991053:
## : ...nr.employed <= 0.4257089:
## : : ...duration <= 0.03497357: no (1213/163)
## : : duration > 0.03497357:
## : : ...contact = telephone: no (150/48)
## : : contact = cellular:
## : : ...duration > 0.050427:
## : : : ...cons.price.idx <= 0.06936867:
## : : : : ...day_of_week in {fri,thu,tue}: no (59/18)
## : : : : day_of_week in {mon,wed}: yes (32/14)
## : : : cons.price.idx > 0.06936867:
## : : : ...education in {basic.6y,basic.9y,high.school,
## : : : : illiterate,
## : : : : university.degree}: yes (288/101)

```



```

##      :      :      :...emp.var.rate <= 0: no (2)
##      :      :      :   emp.var.rate > 0: yes (2)
##      :      :      job = self-employed:
##      :      :      :...marital in {divorced,married}: yes (4)
##      :      :      :   marital in {single,unknown}: no (6/1)
##      :      :      job = student:
##      :      :      :...duration <= 0.04209028: yes (3)
##      :      :      :   duration > 0.04209028: no (2)
##      :      :      job = admin.:
##      :      :      :...day_of_week = fri: yes (8/3)
##      :      :      :   day_of_week = wed: no (12/5)
##      :      :      :   day_of_week = mon:
##      :      :      :...campaign <= 0: no (7)
##      :      :      :   campaign > 0: yes (7/3)
##      :      :      :   day_of_week = thu:
##      :      :      :...campaign <= 0: yes (10/3)
##      :      :      :   campaign > 0: no (4)
##      :      :      :   day_of_week = tue:
##      :      :      :...nr.employed <= 0.2037807: yes (12)
##      :      :      :   nr.employed > 0.2037807:
##      :      :      :...duration <= 0.03924359: yes (2)
##      :      :      :   duration > 0.03924359: no (6)
##      :      :      nr.employed > 0.4257089:
##      :      :      :...age > 0.5308642:
##      :      :      :...duration <= 0.02765352: no (52/5)
##      :      :      :   duration > 0.02765352:
##      :      :      :   :...euribor3m > 0.1736568: yes (42/14)
##      :      :      :   :   euribor3m <= 0.1736568:
##      :      :      :   :   :...marital in {married,single,unknown}: no (9)
##      :      :      :   :   :   marital = divorced:
##      :      :      :   :   :   :...housing in {no,unknown}: no (2)
##      :      :      :   :   :   :   housing = yes: yes (2)
##      :      :      :   :   :   age <= 0.5308642:
##      :      :      :   :   :   :...month in {aug,jul,jun,may,nov,sep}: no (20581/110)
##      :      :      :   :   :   :   month in {apr,dec}:
##      :      :      :   :   :   :   :...euribor3m > 0.1736568: no (1167/99)
##      :      :      :   :   :   :   :   euribor3m <= 0.1736568:
##      :      :      :   :   :   :   :   :...duration <= 0.0351769: no (86/4)
##      :      :      :   :   :   :   :   :   duration > 0.0351769:
##      :      :      :   :   :   :   :   :   :...education in {basic.6y,illiterate,
##      :      :      :   :   :   :   :   :   :   :   professional.course,
##      :      :      :   :   :   :   :   :   :   :   university.degree,
##      :      :      :   :   :   :   :   :   :   :   unknown}: yes (46/18)
##      :      :      :   :   :   :   :   :   :   :   :   education in {basic.9y,high.school}: no (24/8)
##      :      :      :   :   :   :   :   :   :   :   :   :   education = basic.4y:
##      :      :      :   :   :   :   :   :   :   :   :   :   :...age <= 0.1111111: no (2)
##      :      :      :   :   :   :   :   :   :   :   :   :   :   age > 0.1111111: yes (3)
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   month in {mar,oct}:
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :...duration <= 0.01911346: no (59/5)
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   duration > 0.01911346:
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :...campaign > 0.05454545:
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :   :...duration <= 0.05002033: no (11)
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   duration > 0.05002033: yes (2)
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   campaign <= 0.05454545:
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :...month = oct:
##      :      :      :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :   :...loan in {no,unknown}: yes (27/2)

```

```

##      :      :   loan = yes: no (1)
##      :      month = mar:
##      :      :...default = yes: yes (0)
##      :      default = unknown:
##      :      :...job in {admin.,blue-collar,entrepreneur,
##      :      :      :      housemaid,management,retired,
##      :      :      :      self-employed,services,student,
##      :      :      :      technician,unknown}: no (3)
##      :      :   job = unemployed: yes (1)
##      :      default = no:
##      :      :...duration > 0.03761692: yes (49/10)
##      :      duration <= 0.03761692:
##      :      :...marital = divorced: yes (1)
##      :      marital in {single,
##      :      :      :      unknown}: no (35/11)
##      :      marital = married:
##      :      :...housing in {no,
##      :      :      :      unknown}: no (9/3)
##      :      :      housing = yes: yes (13/4)
## duration > 0.07991053:
## :...nr.employed <= 0.4257089:
##      :...emp.var.rate > 0.1041667:
##      :      :...loan in {unknown,yes}: yes (42/6)
##      :      :      loan = no:
##      :      :      :...poutcome = nonexistent: yes (125/26)
##      :      :      poutcome = failure:
##      :      :      :...emp.var.rate <= 0.3541667:
##      :      :      :...campaign <= 0.05454545: yes (40/8)
##      :      :      :      campaign > 0.05454545: no (3)
##      :      :      emp.var.rate > 0.3541667:
##      :      :      :...marital = divorced: yes (4)
##      :      :      marital in {married,single,unknown}: no (17/5)
##      :      emp.var.rate <= 0.1041667:
##      :      :...loan = unknown: yes (12/4)
##      :      loan = yes:
##      :      :...marital in {divorced,single,unknown}: no (11/1)
##      :      :      marital = married:
##      :      :      :...month in {aug,nov}: yes (8/1)
##      :      :      month in {apr,jul,mar,may,oct}: no (4)
##      :      :      month = dec:
##      :      :      :...duration <= 0.101464: yes (2)
##      :      :      :      duration > 0.101464: no (2)
##      :      :      month = jun:
##      :      :      :...day_of_week in {mon,thu}: yes (3)
##      :      :      :      day_of_week in {fri,tue,wed}: no (5/1)
##      :      :      month = sep:
##      :      :      :...duration <= 0.1122407: yes (2)
##      :      :      :      duration > 0.1122407: no (4)
##      :      loan = no:
##      :      :...cons.price.idx > 0.1745908: yes (87/23)
##      :      cons.price.idx <= 0.1745908:
##      :      :...contact = telephone:
##      :      :      :...marital in {divorced,single}: yes (11/4)
##      :      :      :      marital in {married,unknown}: no (15/2)
##      :      :      contact = cellular:
##      :      :      :...duration <= 0.09577064: yes (64/14)

```



```

##      :      :      :      default = unknown: yes (5/1)
##      :      :      :      job = management:
##      :      :      :      ...marital in {married,unknown}: yes (38/12)
##      :      :      :      marital = single: no (9/3)
##      :      :      :      marital = divorced:
##      :      :      :      ...education = high.school: no (1)
##      :      :      :      education in {basic.4y,basic.6y,basic.9y,
##      :      :      :      illiterate,professional.course,
##      :      :      :      university.degree,
##      :      :      :      unknown}: yes (4)
##      :      :      :      job = technician:
##      :      :      :      ...month in {dec,jun,mar,may,oct,sep}: yes (13/3)
##      :      :      :      month = apr:
##      :      :      :      ...campaign <= 0.01818182: yes (5)
##      :      :      :      :      campaign > 0.01818182: no (2)
##      :      :      :      month = aug:
##      :      :      :      ...loan in {no,unknown}: yes (30/11)
##      :      :      :      :      loan = yes: no (5)
##      :      :      :      month = jul:
##      :      :      :      ...day_of_week in {fri,thu,tue,wed}: no (24/8)
##      :      :      :      :      day_of_week = mon: yes (5)
##      :      :      :      month = nov:
##      :      :      :      ...day_of_week in {fri,mon,tue}: yes (6/1)
##      :      :      :      :      day_of_week in {thu,wed}: no (9/1)
##      :      :      :      job = unemployed:
##      :      :      :      ...day_of_week in {mon,tue,wed}: yes (6)
##      :      :      :      :      day_of_week in {fri,thu}:
##      :      :      :      :      ...loan in {no,unknown}: no (4)
##      :      :      :      :      loan = yes: yes (1)
##      :      :      :      contact = telephone:
##      :      :      :      ...month in {apr,aug,dec,mar,oct,sep}: yes (7/1)
##      :      :      :      :      month = jul:
##      :      :      :      :      ...campaign <= 0.09090909: no (16/5)
##      :      :      :      :      :      campaign > 0.09090909: yes (4)
##      :      :      :      :      month = nov:
##      :      :      :      :      ...duration <= 0.2350549: yes (4)
##      :      :      :      :      :      duration > 0.2350549: no (4)
##      :      :      :      :      month = jun:
##      :      :      :      :      ...job = housemaid: no (3/1)
##      :      :      :      :      :      job in {student,technician,unemployed,
##      :      :      :      :      :      :      unknown}: yes (20/7)
##      :      :      :      :      :      job = admin.:
##      :      :      :      :      :      ...day_of_week in {fri,wed}: yes (8)
##      :      :      :      :      :      :      day_of_week in {mon,thu,tue}: no (17/6)
##      :      :      :      :      :      job = entrepreneur:
##      :      :      :      :      :      ...duration <= 0.2248882: no (7/1)
##      :      :      :      :      :      :      duration > 0.2248882: yes (4)
##      :      :      :      :      :      job = management:
##      :      :      :      :      :      ...age <= 0.3950617: yes (5)
##      :      :      :      :      :      :      age > 0.3950617: no (3)
##      :      :      :      :      :      job = retired:
##      :      :      :      :      :      ...marital in {divorced,married,unknown}: yes (4)
##      :      :      :      :      :      :      marital = single: no (1)
##      :      :      :      :      :      job = self-employed:
##      :      :      :      :      :      ...age <= 0.2469136: yes (2)
##      :      :      :      :      :      :      age > 0.2469136: no (2)

```

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##      :      :      job = services:
##      :      :      ...campaign <= 0.01818182: no (2)
##      :      :      :      campaign > 0.01818182: yes (3)
##      :      :      job = blue-collar:
##      :      :      ...marital = unknown: yes (0)
##      :      :      marital = divorced: no (3/1)
##      :      :      marital = single:
##      :      :      ...housing in {no,unknown}: no (5)
##      :      :      :      housing = yes: yes (2)
##      :      :      marital = married:
##      :      :      ...euribor3m > 0.9698481: yes (21/5)
##      :      :      euribor3m <= 0.9698481: [S1]
##      :      month = may:
##      :      ...education = illiterate: no (1)
##      :      education = professional.course: yes (17/5)
##      :      education = basic.6y:
##      :      ...default in {no,yes}: yes (9/2)
##      :      :      default = unknown: no (9/3)
##      :      education = unknown:
##      :      ...default in {unknown,yes}: yes (4)
##      :      :      default = no:
##      :      :      ...age <= 0.2839506: no (5)
##      :      :      age > 0.2839506: yes (3)
##      :      education = high.school:
##      :      ...job in {entrepreneur,technician}: yes (2)
##      :      :      job in {housemaid,management,retired,
##      :      :      :      self-employed,student,unemployed,
##      :      :      :      unknown}: no (6/3)
##      :      :      job = blue-collar:
##      :      :      ...marital in {divorced,married,
##      :      :      :      :      unknown}: yes (4)
##      :      :      :      marital = single: no (2)
##      :      :      job = services:
##      :      :      ...campaign <= 0.01818182: no (17/4)
##      :      :      :      campaign > 0.01818182: yes (6/1)
##      :      :      job = admin.:
##      :      :      ...marital in {divorced,unknown}: no (0)
##      :      :      marital = married:
##      :      :      ...duration <= 0.249085: no (6)
##      :      :      :      duration > 0.249085: yes (3/1)
##      :      :      marital = single:
##      :      :      ...default in {no,yes}: yes (7/1)
##      :      :      default = unknown: no (1)
##      :      education = basic.4y:
##      :      ...euribor3m <= 0.9571525:
##      :      :      ...job in {admin.,blue-collar,housemaid,
##      :      :      :      :      management,retired,self-employed,
##      :      :      :      :      student,technician,unemployed,
##      :      :      :      :      unknown}: no (8)
##      :      :      :      job in {entrepreneur,services}: yes (2)
##      :      :      euribor3m > 0.9571525:
##      :      :      ...day_of_week = tue: no (1)
##      :      :      day_of_week = wed: yes (4)
##      :      :      day_of_week = mon:
##      :      :      ...campaign <= 0: yes (2)
##      :      :      :      campaign > 0: no (2)

```

```

##      :      :      day_of_week = thu:
##      :      :      :...marital = divorced: yes (1)
##      :      :      :   marital in {married,single,
##      :      :      :      unknown}: no (4)
##      :      :      day_of_week = fri:
##      :      :      :...campaign > 0: yes (2)
##      :      :      :   campaign <= 0:
##      :      :      :...loan in {no,unknown}: no (3)
##      :      :      :   loan = yes: yes (1)
##      :      :      education = basic.9y:
##      :      :      :...age > 0.3209876: no (12)
##      :      :      :   age <= 0.3209876:
##      :      :      :...duration > 0.2767385: yes (5)
##      :      :      :   duration <= 0.2767385:
##      :      :      :...housing in {unknown,yes}: no (10/3)
##      :      :      :   housing = no:
##      :      :      :...duration <= 0.2185848: yes (6/1)
##      :      :      :   duration > 0.2185848: no (9/2)
##      :      :      education = university.degree:
##      :      :      :...duration > 0.3186255: yes (6)
##      :      :      :   duration <= 0.3186255:
##      :      :      :...euribor3m > 0.9578327: yes (9/3)
##      :      :      :   euribor3m <= 0.9578327:
##      :      :      :...age <= 0.3333333: no (28/6)
##      :      :      :   age > 0.3333333:
##      :      :      :...euribor3m <= 0.9571525: no (5/1)
##      :      :      :   euribor3m > 0.9571525: yes (5/1)
##      :      :      duration <= 0.1699878:
##      :      :      :...contact = telephone: no (337/91)
##      :      :      :   contact = cellular:
##      :      :      :...default in {unknown,yes}: no (111/36)
##      :      :      :   default = no:
##      :      :      :...euribor3m <= 0.1736568: yes (120/42)
##      :      :      :   euribor3m > 0.1736568:
##      :      :      :...euribor3m <= 0.1838585: no (38/5)
##      :      :      :   euribor3m > 0.1838585:
##      :      :      :...marital = unknown: no (1)
##      :      :      :   marital = divorced:
##      :      :      :...day_of_week = thu: no (8/4)
##      :      :      :   :   day_of_week = wed: yes (9)
##      :      :      :   :   day_of_week = fri:
##      :      :      :   :   :...cons.price.idx <= 0.4844115: yes (2)
##      :      :      :   :   :   cons.price.idx > 0.4844115: no (4)
##      :      :      :   :   :   day_of_week = mon: [S2]
##      :      :      :   :   :   day_of_week = tue:
##      :      :      :   :   :...age <= 0.3333333: yes (7)
##      :      :      :   :   :   age > 0.3333333: no (6/2)
##      :      :      :   marital = married:
##      :      :      :...job in {blue-collar,entrepreneur,
##      :      :      :   :   :   housemaid,retired,student,
##      :      :      :   :   :   unknown}: no (53/18)
##      :      :      :   :   :   job = self-employed:
##      :      :      :   :   :...loan in {no,unknown}: no (7/1)
##      :      :      :   :   :   loan = yes: yes (2)
##      :      :      :   :   :   job = services:
##      :      :      :   :   :...emp.var.rate <= 0.6875: no (5/1)

```

```

##           :   :   emp.var.rate > 0.6875: yes (13/2)
##           :   job = technician:
##           :   :...age <= 0.2962963: yes (23/10)
##           :   :   age > 0.2962963: no (8)
##           :   job = unemployed:
##           :   :...cons.price.idx <= 0.4844115: yes (2)
##           :   :   cons.price.idx > 0.4844115: no (3)
##           :   job = management:
##           :   :...day_of_week in {fri,
##           :   :   :   mon}: no (8/3)
##           :   :   day_of_week = wed: yes (3)
##           :   :   day_of_week = thu:
##           :   :   :...emp.var.rate <= 0.6875: yes (2)
##           :   :   :   emp.var.rate > 0.6875: no (3)
##           :   :   day_of_week = tue:
##           :   :   :...emp.var.rate <= 0.6875: no (3)
##           :   :   :   emp.var.rate > 0.6875: yes (2)
##           :   job = admin.:
##           :   :...cons.price.idx > 0.4844115: yes (16/3)
##           :   :   cons.price.idx <= 0.4844115:
##           :   :   :...duration <= 0.1612444: no (25/5)
##           :   :   :   duration > 0.1612444: [S3]
##           marital = single:
##           :...campaign > 0.05454545: no (8)
##           :   campaign <= 0.05454545:
##           :   :...campaign > 0.03636364: yes (5)
##           :   :   campaign <= 0.03636364: [S4]
##
## SubTree [S1]
##
## education in {basic.4y,basic.6y,high.school,illiterate,professional.course,
## :   university.degree,unknown}: no (6/1)
## education = basic.9y:
## :...housing in {no,unknown}: yes (3)
##   housing = yes: no (1)
##
## SubTree [S2]
##
## education in {basic.4y,basic.6y,basic.9y,high.school,illiterate,
## :   professional.course,unknown}: no (3)
## education = university.degree: yes (1)
##
## SubTree [S3]
##
## loan in {no,unknown}: yes (3)
## loan = yes: no (1)
##
## SubTree [S4]
##
## job in {retired,self-employed,unemployed,unknown}: no (0)
## job in {entrepreneur,housemaid,student}: yes (5/1)
## job = admin.:
## :...campaign <= 0: no (13/3)
## :   campaign > 0: yes (9/2)
## job = blue-collar:
## :...duration <= 0.1667344: no (8)

```

```

## : duration > 0.1667344: yes (2)
## job = management:
## :...day_of_week = thu: no (3/1)
## : day_of_week in {fri,mon,tue,wed}: yes (2)
## job = services:
## :...day_of_week in {fri,mon}: yes (3)
## : day_of_week in {thu,tue,wed}: no (6/1)
## job = technician:
## :...loan in {unknown,yes}: yes (4)
## loan = no:
## :...education in {basic.4y,basic.6y,basic.9y,high.school,illiterate,
## : professional.course,unknown}: no (10/3)
## education = university.degree:
## :...housing = no: no (2)
## housing in {unknown,yes}: yes (3)
##
##
## Evaluation on training data (30891 cases):
##
## Decision Tree
## -----
## Size      Errors
##
## 284 1990( 6.4%)  <<
##
## (a)  (b)  <-classified as
## ---- ----
## 26717 694  (a): class no
## 1296 2184  (b): class yes
##
##
## Attribute usage:
##
## 100.00% duration
## 100.00% poutcome
## 99.22% nr.employed
## 83.36% month
## 81.80% age
## 10.55% contact
## 6.48% euribor3m
## 4.88% job
## 4.01% education
## 2.70% cons.price.idx
## 2.41% default
## 2.30% loan
## 2.24% campaign
## 2.07% marital
## 2.05% emp.var.rate
## 1.50% day_of_week
## 0.78% cons.conf.idx
## 0.39% housing
## 0.32% pdays
##
##
## Time: 0.2 secs

```



```

# Applying model to the training set which classifies all the observations in training set
# as either "yes" or "no"
tree_pred <- predict(decision_tree, test_data[-21])
str(tree_pred)

## Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
# Evaluating model performance by comparing the predicted variable with true labels

# The model has an accuracy of 91.32% and p-value is < 2.2e-16 which implies that the model
# is performing well. The kappa value is 0.533 which indicates a moderate agreement between
# true and predicted values. The sensitivity and specificity of the model are 0.53 and 0.96,
# which are the false negative and false positive rates respectively
CrossTable(tree_pred, test_data$y)

```

```

##
##
##      Cell Contents
## |-----|
## |                      N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  10297
##
##
##      | test_data$y
##      tree_pred |      no |      yes | Row Total |
## -----|-----|-----|-----|
##      no |      8781 |      538 |      9319 |
##      |      31.680 |      249.531 |      |
##      |      0.942 |      0.058 |      0.905 |
##      |      0.961 |      0.464 |      |
##      |      0.853 |      0.052 |      |
## -----|-----|-----|-----|
##      yes |      356 |      622 |      978 |
##      |      301.863 |      2377.692 |      |
##      |      0.364 |      0.636 |      0.095 |
##      |      0.039 |      0.536 |      |
##      |      0.035 |      0.060 |      |
## -----|-----|-----|-----|
## Column Total |      9137 |      1160 |      10297 |
##      |      0.887 |      0.113 |      |
## -----|-----|-----|-----|
##
##

```

```

confusionMatrix(tree_pred,test_data$y, positive = "yes")

```

```

## Confusion Matrix and Statistics
##
##      Reference
## Prediction  no  yes
##      no  8781  538

```

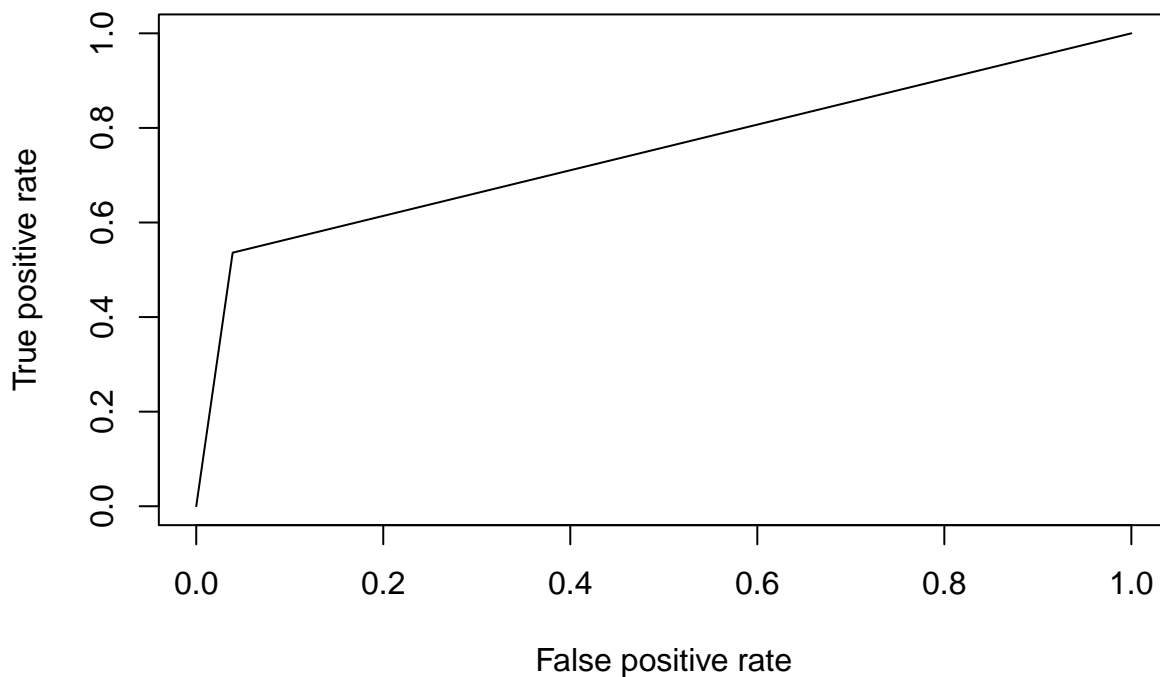
```
##          yes  356  622
##
##          Accuracy : 0.9132
##          95% CI : (0.9076, 0.9185)
##    No Information Rate : 0.8873
##    P-Value [Acc > NIR] : < 2.2e-16
##
##          Kappa : 0.5338
## Mcnemar's Test P-Value : 1.417e-09
##
##          Sensitivity : 0.53621
##          Specificity : 0.96104
##    Pos Pred Value : 0.63599
##    Neg Pred Value : 0.94227
##          Prevalence : 0.11265
##    Detection Rate : 0.06041
##    Detection Prevalence : 0.09498
##    Balanced Accuracy : 0.74862
##
##    'Positive' Class : yes
##
```

```
dt_accuracy <- confusionMatrix(tree_pred,test_data$y, positive = "yes")$overall[[1]]
dt_accuracy <- dt_accuracy*100
dt_accuracy
```

```
## [1] 91.31786
```

```
# The ROC curve suggests that the model is doing a fine job in predicting the true negatives
# and false positives with a area under the curve value of 0.74
pred_dt <- prediction(predictions = as.numeric(tree_pred), labels = as.numeric(test_data$y))
perf_dt <- performance(pred_dt,measure = "tpr", x.measure = "fpr")
plot(perf_dt, main="Decision Tree 1")
```

Decision Tree 1



```
perf_auc <- performance(pred_dt, measure = "auc")
dt_auc <- unlist(perf_auc@y.values)
dt_auc
```

```
## [1] 0.7486222
```

```
# We can improve performance of the model in classifying FP and FN and thereby increasing
# the value of auc by assigning cost or penalty for the making a FP or FN mistake. Here we
# assigned more penalty for FN than FP because it is better to make few extra calls for
# the people who won't actually take the plan, than classifying the person who would
# actually take the subscription as "no" and avoid contacting him altogether
```

```
# Creating cost error matrix
matrix_dimensions <- list(c("no", "yes"), c("no", "yes"))
names(matrix_dimensions) <- c("predicted", "actual")
matrix_dimensions
```

```
## $predicted
## [1] "no" "yes"
##
## $actual
## [1] "no" "yes"
```

```
error_cost <- matrix(c(0, 1, 5, 0), nrow = 2, dimnames = matrix_dimensions)
error_cost
```

```
##          actual
## predicted no yes
##      no    0  5
##      yes   1  0
```

```
# Training a decision tree model using the error_cost matrix
set.seed(141)
decision_tree_2 <- C5.0(train_data[-21], train_data$y, trails=20, costs=error_cost)
summary(decision_tree)
```

```
##
## Call:
## C5.0.default(x = train_data[-21], y = train_data$y, trails = 20)
##
##
## C5.0 [Release 2.07 GPL Edition]          Sun Dec 10 17:34:15 2017
## -----
##
## Class specified by attribute `outcome'
##
## Read 30891 cases (21 attributes) from undefined.data
##
## Decision tree:
##
## poutcome = success:
## ...duration <= 0.03273689:
## :   ...cons.conf.idx <= 0.376569: no (69/3)
## :   :   cons.conf.idx > 0.376569:
## :   :   ...campaign > 0.01818182:
## :   :   :   ...marital = divorced: yes (3/1)
## :   :   :   marital in {married,single,unknown}: no (25/1)
## :   :   campaign <= 0.01818182:
## :   :   :   ...month in {jun,oct}: no (39/13)
```

```

## : : month = apr:
## : : ...housing in {no,unknown}: no (3)
## : : : housing = yes: yes (1)
## : : month = dec:
## : : ...duration <= 0.02806019: no (3)
## : : : duration > 0.02806019: yes (2)
## : : month = jul:
## : : ...duration <= 0.02704351: no (6)
## : : : duration > 0.02704351: yes (2)
## : : month = mar:
## : : ...housing in {no,unknown}: yes (5)
## : : : housing = yes: no (5/1)
## : : month = may:
## : : ...duration <= 0.02704351: no (3)
## : : : duration > 0.02704351: yes (3)
## : : month = nov:
## : : ...euribor3m <= 0.01836318: yes (14/1)
## : : : euribor3m > 0.01836318: no (2)
## : : month = sep:
## : : ...housing = no: yes (4)
## : : : housing in {unknown,yes}: no (11/4)
## : : month = aug:
## : : ...age <= 0.3580247:
## : : : ...euribor3m <= 0.04919519: yes (7/2)
## : : : : euribor3m > 0.04919519: no (18/2)
## : : : age > 0.3580247:
## : : : ...housing in {no,unknown}: no (3)
## : : : : housing = yes: yes (14/6)
## : duration > 0.03273689:
## : ...nr.employed <= 0.4257089: yes (649/116)
## : nr.employed > 0.4257089:
## : : ...month = mar: yes (2)
## : : month in {aug,dec,jul,jun,nov,oct,sep}: no (15/2)
## : : month = apr:
## : : ...pdays <= 0.007007007: yes (30/7)
## : : : pdays > 0.007007007: no (6/1)
## : : month = may:
## : : ...job in {entrepreneur,housemaid,management,retired,
## : : : self-employed,student,unknown}: no (10)
## : : : job in {technician,unemployed}: yes (15/4)
## : : : job = admin.:
## : : : ...day_of_week in {fri,wed}: yes (6/1)
## : : : : day_of_week in {mon,tue}: no (7)
## : : : : day_of_week = thu:
## : : : : ...housing = no: yes (1)
## : : : : : housing in {unknown,yes}: no (3)
## : : : job = services:
## : : : ...education in {basic.4y,basic.6y,basic.9y,illiterate,
## : : : : : professional.course,unknown}: yes (3)
## : : : : : education = university.degree: no (1)
## : : : : : education = high.school:
## : : : : : ...housing = no: yes (2)
## : : : : : : housing in {unknown,yes}: no (2)
## : : : job = blue-collar:
## : : : ...duration <= 0.09109394: no (15/1)
## : : : duration > 0.09109394:

```



```

## : : education = professional.course:
## : : :...job in {admin.,entrepreneur,housemaid,management,
## : : : : services,student,unknown}: no (7/2)
## : : : job in {blue-collar,self-employed,
## : : : : unemployed}: yes (9/1)
## : : : job = retired:
## : : : :...campaign <= 0: yes (4)
## : : : : campaign > 0: no (3)
## : : : job = technician:
## : : : :...loan = no: no (26/8)
## : : : : loan in {unknown,yes}: yes (5/1)
## : : education = university.degree:
## : : :...poutcome = failure:
## : : : :...pdays <= 0.006006006: yes (4)
## : : : : pdays > 0.006006006: no (58/16)
## : : poutcome = nonexistent:
## : : :...job in {blue-collar,entrepreneur,management,
## : : : : technician,unknown}: no (40/14)
## : : : job in {housemaid,services,
## : : : : unemployed}: yes (4)
## : : : job = retired:
## : : : :...emp.var.rate <= 0: no (2)
## : : : : emp.var.rate > 0: yes (2)
## : : : job = self-employed:
## : : : :...marital in {divorced,married}: yes (4)
## : : : : marital in {single,unknown}: no (6/1)
## : : : job = student:
## : : : :...duration <= 0.04209028: yes (3)
## : : : : duration > 0.04209028: no (2)
## : : : job = admin.:
## : : : :...day_of_week = fri: yes (8/3)
## : : : : day_of_week = wed: no (12/5)
## : : : : day_of_week = mon:
## : : : : :...campaign <= 0: no (7)
## : : : : : campaign > 0: yes (7/3)
## : : : : day_of_week = thu:
## : : : : :...campaign <= 0: yes (10/3)
## : : : : : campaign > 0: no (4)
## : : : : day_of_week = tue:
## : : : : :...nr.employed <= 0.2037807: yes (12)
## : : : : : nr.employed > 0.2037807:
## : : : : :...duration <= 0.03924359: yes (2)
## : : : : : duration > 0.03924359: no (6)
## : nr.employed > 0.4257089:
## : :...age > 0.5308642:
## : : :...duration <= 0.02765352: no (52/5)
## : : : : duration > 0.02765352:
## : : : : :...euribor3m > 0.1736568: yes (42/14)
## : : : : : euribor3m <= 0.1736568:
## : : : : :...marital in {married,single,unknown}: no (9)
## : : : : : marital = divorced:
## : : : : :...housing in {no,unknown}: no (2)
## : : : : : housing = yes: yes (2)
## : age <= 0.5308642:
## : :...month in {aug,jul,jun,may,nov,sep}: no (20581/110)
## : : month in {apr,dec}:

```

```

## : :...euribor3m > 0.1736568: no (1167/99)
## : : euribor3m <= 0.1736568:
## : : :...duration <= 0.0351769: no (86/4)
## : : : duration > 0.0351769:
## : : :...education in {basic.6y,illiterate,
## : : : : professional.course,
## : : : : university.degree,
## : : : : unknown}: yes (46/18)
## : : : education in {basic.9y,high.school}: no (24/8)
## : : : education = basic.4y:
## : : :...age <= 0.1111111: no (2)
## : : : age > 0.1111111: yes (3)
## : month in {mar,oct}:
## : :...duration <= 0.01911346: no (59/5)
## : : duration > 0.01911346:
## : : :...campaign > 0.05454545:
## : : :...duration <= 0.05002033: no (11)
## : : : : duration > 0.05002033: yes (2)
## : : : campaign <= 0.05454545:
## : : :...month = oct:
## : : :...loan in {no,unknown}: yes (27/2)
## : : : : loan = yes: no (1)
## : : : month = mar:
## : : :...default = yes: yes (0)
## : : : default = unknown:
## : : :...job in {admin.,blue-collar,entrepreneur,
## : : : : : housemaid,management,retired,
## : : : : : self-employed,services,student,
## : : : : : technician,unknown}: no (3)
## : : : : job = unemployed: yes (1)
## : : : default = no:
## : : :...duration > 0.03761692: yes (49/10)
## : : : duration <= 0.03761692:
## : : :...marital = divorced: yes (1)
## : : : : marital in {single,
## : : : : : unknown}: no (35/11)
## : : : : marital = married:
## : : : :...housing in {no,
## : : : : : : unknown}: no (9/3)
## : : : : : housing = yes: yes (13/4)
## : duration > 0.07991053:
## : :...nr.employed <= 0.4257089:
## : : :...emp.var.rate > 0.1041667:
## : : : : :...loan in {unknown,yes}: yes (42/6)
## : : : : : : loan = no:
## : : : : : : :...poutcome = nonexistent: yes (125/26)
## : : : : : : : poutcome = failure:
## : : : : : : :...emp.var.rate <= 0.3541667:
## : : : : : : :...campaign <= 0.05454545: yes (40/8)
## : : : : : : : : campaign > 0.05454545: no (3)
## : : : : : : : emp.var.rate > 0.3541667:
## : : : : : : :...marital = divorced: yes (4)
## : : : : : : : : marital in {married,single,unknown}: no (17/5)
## : : : emp.var.rate <= 0.1041667:
## : : : :...loan = unknown: yes (12/4)
## : : : : loan = yes:

```



```

##      :      :      retired,self-employed,services,student,
##      :      :      technician,unknown}: yes (12)
##      :      :      job in {blue-collar,unemployed}: no (2)
## duration > 0.1309475:
##      :...duration > 0.1699878:
##      :...contact = cellular:
##      :      :...job in {admin.,blue-collar,retired,self-employed,
##      :      :      :      student,unknown}: yes (386/145)
##      :      :      job = housemaid:
##      :      :      :...education in {basic.4y,high.school,illiterate,
##      :      :      :      :      professional.course,
##      :      :      :      :      unknown}: no (9/2)
##      :      :      :      education in {basic.6y,basic.9y,
##      :      :      :      :      university.degree}: yes (9/2)
##      :      :      job = services:
##      :      :      :...day_of_week = fri: no (13/3)
##      :      :      :      day_of_week in {mon,thu,tue,wed}: yes (45/12)
##      :      :      job = entrepreneur:
##      :      :      :...campaign <= 0: yes (8/1)
##      :      :      :      campaign > 0:
##      :      :      :      :...default in {no,yes}: no (15/4)
##      :      :      :      :      default = unknown: yes (5/1)
##      :      :      job = management:
##      :      :      :...marital in {married,unknown}: yes (38/12)
##      :      :      :      marital = single: no (9/3)
##      :      :      :      marital = divorced:
##      :      :      :      :...education = high.school: no (1)
##      :      :      :      :      education in {basic.4y,basic.6y,basic.9y,
##      :      :      :      :      :      illiterate,professional.course,
##      :      :      :      :      :      university.degree,
##      :      :      :      :      :      unknown}: yes (4)
##      :      :      job = technician:
##      :      :      :...month in {dec,jun,mar,may,oct,sep}: yes (13/3)
##      :      :      :      month = apr:
##      :      :      :      :...campaign <= 0.01818182: yes (5)
##      :      :      :      :      campaign > 0.01818182: no (2)
##      :      :      :      month = aug:
##      :      :      :      :...loan in {no,unknown}: yes (30/11)
##      :      :      :      :      loan = yes: no (5)
##      :      :      :      month = jul:
##      :      :      :      :...day_of_week in {fri,thu,tue,wed}: no (24/8)
##      :      :      :      :      day_of_week = mon: yes (5)
##      :      :      :      month = nov:
##      :      :      :      :...day_of_week in {fri,mon,tue}: yes (6/1)
##      :      :      :      :      day_of_week in {thu,wed}: no (9/1)
##      :      :      job = unemployed:
##      :      :      :...day_of_week in {mon,tue,wed}: yes (6)
##      :      :      :      day_of_week in {fri,thu}:
##      :      :      :      :...loan in {no,unknown}: no (4)
##      :      :      :      :      loan = yes: yes (1)
##      :      :      contact = telephone:
##      :      :      :...month in {apr,aug,dec,mar,oct,sep}: yes (7/1)
##      :      :      :      month = jul:
##      :      :      :      :...campaign <= 0.09090909: no (16/5)
##      :      :      :      :      campaign > 0.09090909: yes (4)
##      :      :      :      month = nov:

```

```

##      :      :...duration <= 0.2350549: yes (4)
##      :      :      duration > 0.2350549: no (4)
##      :      month = jun:
##      :      :...job = housemaid: no (3/1)
##      :      :      job in {student,technician,unemployed,
##      :      :      :      :      unknown}: yes (20/7)
##      :      :      job = admin.:
##      :      :      :...day_of_week in {fri,wed}: yes (8)
##      :      :      :      day_of_week in {mon,thu,tue}: no (17/6)
##      :      :      job = entrepreneur:
##      :      :      :...duration <= 0.2248882: no (7/1)
##      :      :      :      duration > 0.2248882: yes (4)
##      :      :      job = management:
##      :      :      :...age <= 0.3950617: yes (5)
##      :      :      :      age > 0.3950617: no (3)
##      :      :      job = retired:
##      :      :      :...marital in {divorced,married,unknown}: yes (4)
##      :      :      :      marital = single: no (1)
##      :      :      job = self-employed:
##      :      :      :...age <= 0.2469136: yes (2)
##      :      :      :      age > 0.2469136: no (2)
##      :      :      job = services:
##      :      :      :...campaign <= 0.01818182: no (2)
##      :      :      :      campaign > 0.01818182: yes (3)
##      :      :      job = blue-collar:
##      :      :      :...marital = unknown: yes (0)
##      :      :      :      marital = divorced: no (3/1)
##      :      :      :      marital = single:
##      :      :      :      :...housing in {no,unknown}: no (5)
##      :      :      :      :      housing = yes: yes (2)
##      :      :      :      marital = married:
##      :      :      :      :...euribor3m > 0.9698481: yes (21/5)
##      :      :      :      :      euribor3m <= 0.9698481: [S1]
##      :      month = may:
##      :      :...education = illiterate: no (1)
##      :      :      education = professional.course: yes (17/5)
##      :      :      education = basic.6y:
##      :      :      :...default in {no,yes}: yes (9/2)
##      :      :      :      default = unknown: no (9/3)
##      :      :      education = unknown:
##      :      :      :...default in {unknown,yes}: yes (4)
##      :      :      :      default = no:
##      :      :      :      :...age <= 0.2839506: no (5)
##      :      :      :      :      age > 0.2839506: yes (3)
##      :      :      education = high.school:
##      :      :      :...job in {entrepreneur,technician}: yes (2)
##      :      :      :      job in {housemaid,management,retired,
##      :      :      :      :      :      self-employed,student,unemployed,
##      :      :      :      :      :      unknown}: no (6/3)
##      :      :      :      job = blue-collar:
##      :      :      :      :...marital in {divorced,married,
##      :      :      :      :      :      :      :      unknown}: yes (4)
##      :      :      :      :      marital = single: no (2)
##      :      :      :      job = services:
##      :      :      :      :...campaign <= 0.01818182: no (17/4)
##      :      :      :      :      campaign > 0.01818182: yes (6/1)

```

```

##      :      :      job = admin.:
##      :      :      :...marital in {divorced,unknown}: no (0)
##      :      :      marital = married:
##      :      :      :...duration <= 0.249085: no (6)
##      :      :      :      duration > 0.249085: yes (3/1)
##      :      :      marital = single:
##      :      :      :...default in {no,yes}: yes (7/1)
##      :      :      default = unknown: no (1)
##      :      education = basic.4y:
##      :      :...euribor3m <= 0.9571525:
##      :      :      :...job in {admin.,blue-collar,housemaid,
##      :      :      :      :      management,retired,self-employed,
##      :      :      :      :      student,technician,unemployed,
##      :      :      :      :      unknown}: no (8)
##      :      :      :      job in {entrepreneur,services}: yes (2)
##      :      :      euribor3m > 0.9571525:
##      :      :      :...day_of_week = tue: no (1)
##      :      :      :      day_of_week = wed: yes (4)
##      :      :      :      day_of_week = mon:
##      :      :      :      :...campaign <= 0: yes (2)
##      :      :      :      :      campaign > 0: no (2)
##      :      :      :      day_of_week = thu:
##      :      :      :      :...marital = divorced: yes (1)
##      :      :      :      :      marital in {married,single,
##      :      :      :      :      :      unknown}: no (4)
##      :      :      :      day_of_week = fri:
##      :      :      :      :...campaign > 0: yes (2)
##      :      :      :      :      campaign <= 0:
##      :      :      :      :      :...loan in {no,unknown}: no (3)
##      :      :      :      :      :      loan = yes: yes (1)
##      :      :      education = basic.9y:
##      :      :      :...age > 0.3209876: no (12)
##      :      :      :      age <= 0.3209876:
##      :      :      :      :...duration > 0.2767385: yes (5)
##      :      :      :      :      duration <= 0.2767385:
##      :      :      :      :      :...housing in {unknown,yes}: no (10/3)
##      :      :      :      :      :      housing = no:
##      :      :      :      :      :      :...duration <= 0.2185848: yes (6/1)
##      :      :      :      :      :      :      duration > 0.2185848: no (9/2)
##      :      :      :      education = university.degree:
##      :      :      :      :...duration > 0.3186255: yes (6)
##      :      :      :      :      duration <= 0.3186255:
##      :      :      :      :      :...euribor3m > 0.9578327: yes (9/3)
##      :      :      :      :      :      euribor3m <= 0.9578327:
##      :      :      :      :      :      :...age <= 0.3333333: no (28/6)
##      :      :      :      :      :      :      age > 0.3333333:
##      :      :      :      :      :      :      :...euribor3m <= 0.9571525: no (5/1)
##      :      :      :      :      :      :      :      euribor3m > 0.9571525: yes (5/1)
##      :      :      :      duration <= 0.1699878:
##      :      :      :      :...contact = telephone: no (337/91)
##      :      :      :      :      contact = cellular:
##      :      :      :      :      :...default in {unknown,yes}: no (111/36)
##      :      :      :      :      :      default = no:
##      :      :      :      :      :      :...euribor3m <= 0.1736568: yes (120/42)
##      :      :      :      :      :      :      euribor3m > 0.1736568:
##      :      :      :      :      :      :      :...euribor3m <= 0.1838585: no (38/5)

```

```

## euribor3m > 0.1838585:
## :...marital = unknown: no (1)
## marital = divorced:
## :...day_of_week = thu: no (8/4)
## : day_of_week = wed: yes (9)
## : day_of_week = fri:
## : :...cons.price.idx <= 0.4844115: yes (2)
## : : cons.price.idx > 0.4844115: no (4)
## : day_of_week = mon: [S2]
## : day_of_week = tue:
## : :...age <= 0.3333333: yes (7)
## : : age > 0.3333333: no (6/2)
## marital = married:
## :...job in {blue-collar,entrepreneur,
## : : housemaid,retired,student,
## : : unknown}: no (53/18)
## : job = self-employed:
## : :...loan in {no,unknown}: no (7/1)
## : : loan = yes: yes (2)
## : job = services:
## : :...emp.var.rate <= 0.6875: no (5/1)
## : : emp.var.rate > 0.6875: yes (13/2)
## : job = technician:
## : :...age <= 0.2962963: yes (23/10)
## : : age > 0.2962963: no (8)
## : job = unemployed:
## : :...cons.price.idx <= 0.4844115: yes (2)
## : : cons.price.idx > 0.4844115: no (3)
## : job = management:
## : :...day_of_week in {fri,
## : : : mon}: no (8/3)
## : : day_of_week = wed: yes (3)
## : : day_of_week = thu:
## : : :...emp.var.rate <= 0.6875: yes (2)
## : : : emp.var.rate > 0.6875: no (3)
## : : day_of_week = tue:
## : : :...emp.var.rate <= 0.6875: no (3)
## : : : emp.var.rate > 0.6875: yes (2)
## : job = admin.:
## : :...cons.price.idx > 0.4844115: yes (16/3)
## : : cons.price.idx <= 0.4844115:
## : : :...duration <= 0.1612444: no (25/5)
## : : : duration > 0.1612444: [S3]
## marital = single:
## :...campaign > 0.05454545: no (8)
## : campaign <= 0.05454545:
## : :...campaign > 0.03636364: yes (5)
## : : campaign <= 0.03636364: [S4]
##
## SubTree [S1]
##
## education in {basic.4y,basic.6y,high.school,illiterate,professional.course,
## : : university.degree,unknown}: no (6/1)
## education = basic.9y:
## :...housing in {no,unknown}: yes (3)
## : housing = yes: no (1)

```

```

##
## SubTree [S2]
##
## education in {basic.4y,basic.6y,basic.9y,high.school,illiterate,
## :           professional.course,unknown}: no (3)
## education = university.degree: yes (1)
##
## SubTree [S3]
##
## loan in {no,unknown}: yes (3)
## loan = yes: no (1)
##
## SubTree [S4]
##
## job in {retired,self-employed,unemployed,unknown}: no (0)
## job in {entrepreneur,housemaid,student}: yes (5/1)
## job = admin.:
## :...campaign <= 0: no (13/3)
## :   campaign > 0: yes (9/2)
## job = blue-collar:
## :...duration <= 0.1667344: no (8)
## :   duration > 0.1667344: yes (2)
## job = management:
## :...day_of_week = thu: no (3/1)
## :   day_of_week in {fri,mon,tue,wed}: yes (2)
## job = services:
## :...day_of_week in {fri,mon}: yes (3)
## :   day_of_week in {thu,tue,wed}: no (6/1)
## job = technician:
## :...loan in {unknown,yes}: yes (4)
##   loan = no:
##   :...education in {basic.4y,basic.6y,basic.9y,high.school,illiterate,
##   :               professional.course,unknown}: no (10/3)
##   education = university.degree:
##   :...housing = no: no (2)
##   housing in {unknown,yes}: yes (3)
##
##
## Evaluation on training data (30891 cases):
##
##   Decision Tree
##   -----
##   Size      Errors
##
##   284 1990( 6.4%)  <<
##
##   (a)  (b)  <-classified as
##   ----  ----
##   26717  694  (a): class no
##   1296  2184  (b): class yes
##
##
## Attribute usage:
##
## 100.00% duration

```

```
## 100.00% poutcome
## 99.22% nr.employed
## 83.36% month
## 81.80% age
## 10.55% contact
## 6.48% euribor3m
## 4.88% job
## 4.01% education
## 2.70% cons.price.idx
## 2.41% default
## 2.30% loan
## 2.24% campaign
## 2.07% marital
## 2.05% emp.var.rate
## 1.50% day_of_week
## 0.78% cons.conf.idx
## 0.39% housing
## 0.32% pdays
```

```
##
##
## Time: 0.2 secs
```

```
# Applying the new model to test set
tree_pred_2 <- predict(decision_tree_2, test_data[-21])
str(tree_pred_2)
```

```
## Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
# The accuracy of the model was slightly reduced to 88.06%. But the value of sensitivity
# is very significantly improved
confusionMatrix(tree_pred_2, test_data$y, positive = "yes")
```

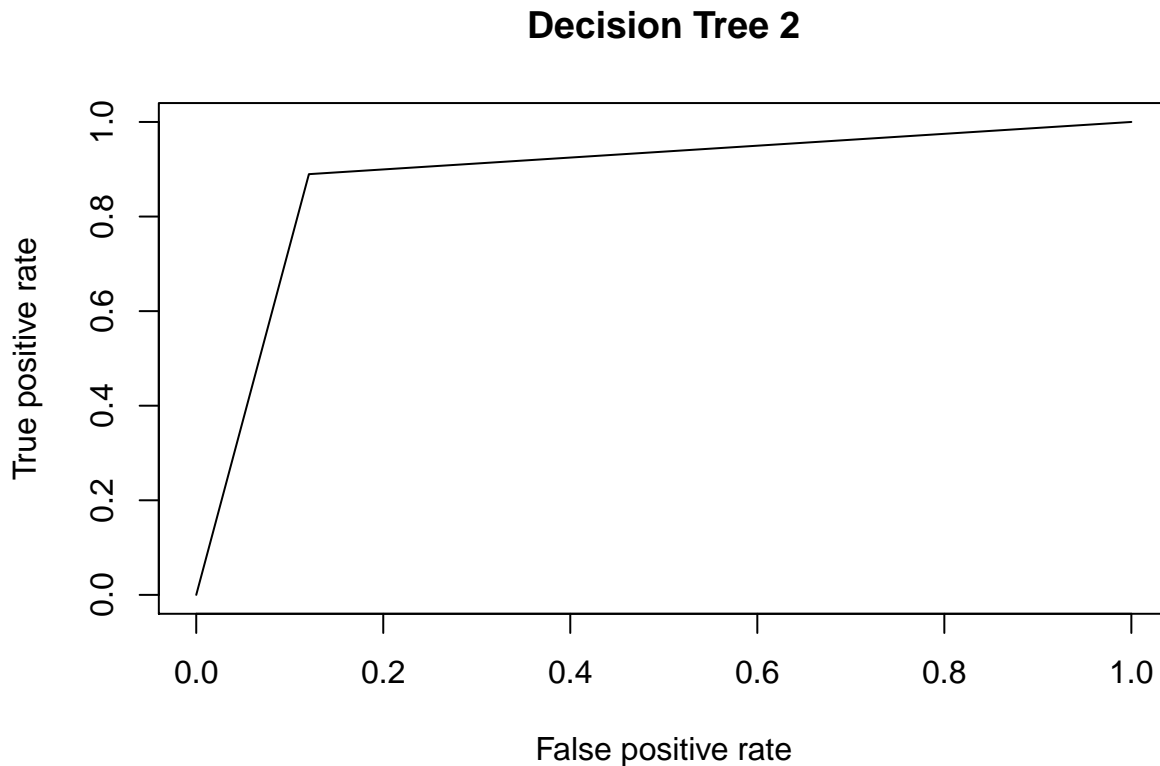
```
## Confusion Matrix and Statistics
```

```
##
##           Reference
## Prediction  no  yes
##          no 8036 128
##          yes 1101 1032
##
##           Accuracy : 0.8806
##           95% CI : (0.8742, 0.8868)
##       No Information Rate : 0.8873
##       P-Value [Acc > NIR] : 0.9843
##
##           Kappa : 0.563
##  McNemar's Test P-Value : <2e-16
##
##           Sensitivity : 0.8897
##           Specificity : 0.8795
##       Pos Pred Value : 0.4838
##       Neg Pred Value : 0.9843
##           Prevalence : 0.1127
##       Detection Rate : 0.1002
##       Detection Prevalence : 0.2071
##       Balanced Accuracy : 0.8846
##
##       'Positive' Class : yes
##
```

```
dt2_accuracy <- confusionMatrix(tree_pred_2, test_data$y, positive = "yes")$overall[[1]]
dt2_accuracy <- dt2_accuracy*100
dt2_accuracy
```

```
## [1] 88.06448
```

```
# The ROC curve also reflects improvement in the prediction of true positives with auc of 0.8845
pred_dt_2 <- prediction(predictions = as.numeric(tree_pred_2), labels = as.numeric(test_data$y))
perf_dt_2 <- performance(pred_dt_2, measure = "tpr", x.measure = "fpr")
plot(perf_dt_2, main="Decision Tree 2")
```



```
perf.auc_dt_2 <- performance(pred_dt_2, measure = "auc")
dt2_auc <- unlist(perf.auc_dt_2@y.values)
dt2_auc
```

```
## [1] 0.8845781
```

```
### Neural Networks ###
```

```
library(nnet)
```

```
set.seed(141)
```

```
# creating a neural network model using training set
```

```
nnet_model <- nnet(y~age + job + marital + education +
                  default + housing + loan + contact +
                  month + day_of_week + duration + campaign +
                  pdays + previous + poutcome + emp.var.rate +
                  cons.price.idx + cons.conf.idx + euribor3m +
                  nr.employed, data=train_data, size=9, decay=0.1)
```

```
## # weights: 496
```

```
## initial value 31333.957381
```

```
## iter 10 value 9011.110826
```

```
## iter 20 value 7669.544914
```

```
## iter 30 value 6741.491465
## iter 40 value 6413.159454
## iter 50 value 6191.163433
## iter 60 value 5943.655987
## iter 70 value 5764.836959
## iter 80 value 5671.171255
## iter 90 value 5595.733635
## iter 100 value 5531.377260
## final value 5531.377260
## stopped after 100 iterations
```

```
# The model has 53 input nodes, 9 hidden nodes and 1 output node
nnet_model$n
```

```
## [1] 53 9 1
```

```
# applying the neural network model to test set
nnet_pred <- predict(nnet_model, test_data[-21], type="class")
str(nnet_pred)
```

```
## chr [1:10297] "no" "no" "no" "no" "no" "no" "no" "no" "no" "no" "no" ...
```

```
# The accuracy of the model is around 91% which is very good. And the kappa value is
# indicating a moderate agreement between predicted and true values.
CrossTable(nnet_pred, test_data$y)
```

```
##
##
##      Cell Contents
## |-----|
## |                      N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table: 10297
##
##
##      | test_data$y
##      nnet_pred |      no |      yes | Row Total |
## -----|-----|-----|-----|
##      no |      8830 |      571 |      9401 |
##      |      28.555 |      224.920 |      |
##      |      0.939 |      0.061 |      0.913 |
##      |      0.966 |      0.492 |      |
##      |      0.858 |      0.055 |      |
## -----|-----|-----|-----|
##      yes |      307 |      589 |      896 |
##      |      299.605 |      2359.905 |      |
##      |      0.343 |      0.657 |      0.087 |
##      |      0.034 |      0.508 |      |
##      |      0.030 |      0.057 |      |
## -----|-----|-----|-----|
## Column Total |      9137 |      1160 |      10297 |
##      |      0.887 |      0.113 |      |
## -----|-----|-----|-----|
```



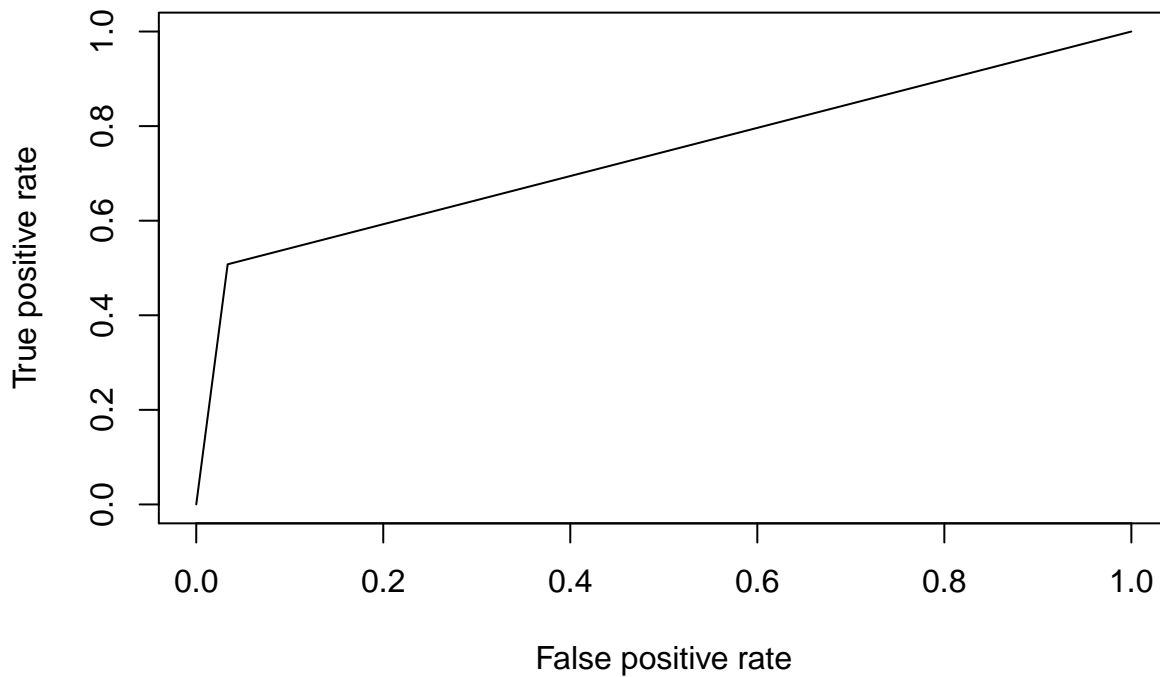
```
##
##
confusionMatrix(nnet_pred,test_data$y, positive = "yes")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no  yes
##           no 8830 571
##           yes 307 589
##
##           Accuracy : 0.9147
##           95% CI : (0.9092, 0.9201)
##           No Information Rate : 0.8873
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.5265
##           McNemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.50776
##           Specificity : 0.96640
##           Pos Pred Value : 0.65737
##           Neg Pred Value : 0.93926
##           Prevalence : 0.11265
##           Detection Rate : 0.05720
##           Detection Prevalence : 0.08702
##           Balanced Accuracy : 0.73708
##
##           'Positive' Class : yes
##
nnet_accuracy <- confusionMatrix(nnet_pred,test_data$y, positive = "yes")$overall[[1]]
nn_accuracy <- nnet_accuracy*100
nn_accuracy

## [1] 91.47324

# Building ROC curve and calculating AUC of the predicted and true values indicating the
# relationship between true positive rate and false positive rate.
nnet_pred_fac <- as.factor(nnet_pred)
pred_nn <- prediction(predictions = as.numeric(nnet_pred_fac), labels = as.numeric(test_data$y))
perf_nn <- performance(pred_nn,measure = "tpr", x.measure = "fpr")
plot(perf_nn, main="Neural Net 1")
```

Neural Net 1



```
perf.auc_nn <- performance(pred_nn, measure = "auc")
nn_auc <- unlist(perf.auc_nn@y.values)
nn_auc
```

```
## [1] 0.7370795
```

```
# Lets try to improve the model performance by using the function pcaNNet which applies
# principal component analysis to the variables before building a neural network model.
set.seed(141)
```

```
nnet_model_2 <- pcaNNet(y~age + job + marital + education +
  default + housing + loan + contact +
  month + day_of_week + duration + campaign +
  pdays + previous + poutcome + emp.var.rate +
  cons.price.idx + cons.conf.idx + euribor3m +
  nr.employed, data=train_data, size=8, decay=0.1)
```

```
## # weights: 386
## initial value 21417.939395
## iter 10 value 7230.132920
## iter 20 value 6255.473857
## iter 30 value 5607.495900
## iter 40 value 4768.984514
## iter 50 value 3981.698700
## iter 60 value 3767.468181
## iter 70 value 3662.719354
## iter 80 value 3578.469377
## iter 90 value 3525.404344
## iter 100 value 3480.951714
## final value 3480.951714
## stopped after 100 iterations
```

```
# predicting the target variable of the training set using the model
nnet_pred_2 <- predict(nnet_model_2, test_data[, -21], type="class")
str(nnet_pred_2)
```

```
## chr [1:10297] "no" "no" "no" "no" "no" "no" "no" "no" "no" "no" "no" ...
# The sensitivity of the model fairly increased but it is still less efficient compared to
# the decision tree model
confusionMatrix(nnet_pred_2,test_data$y, positive = "yes")

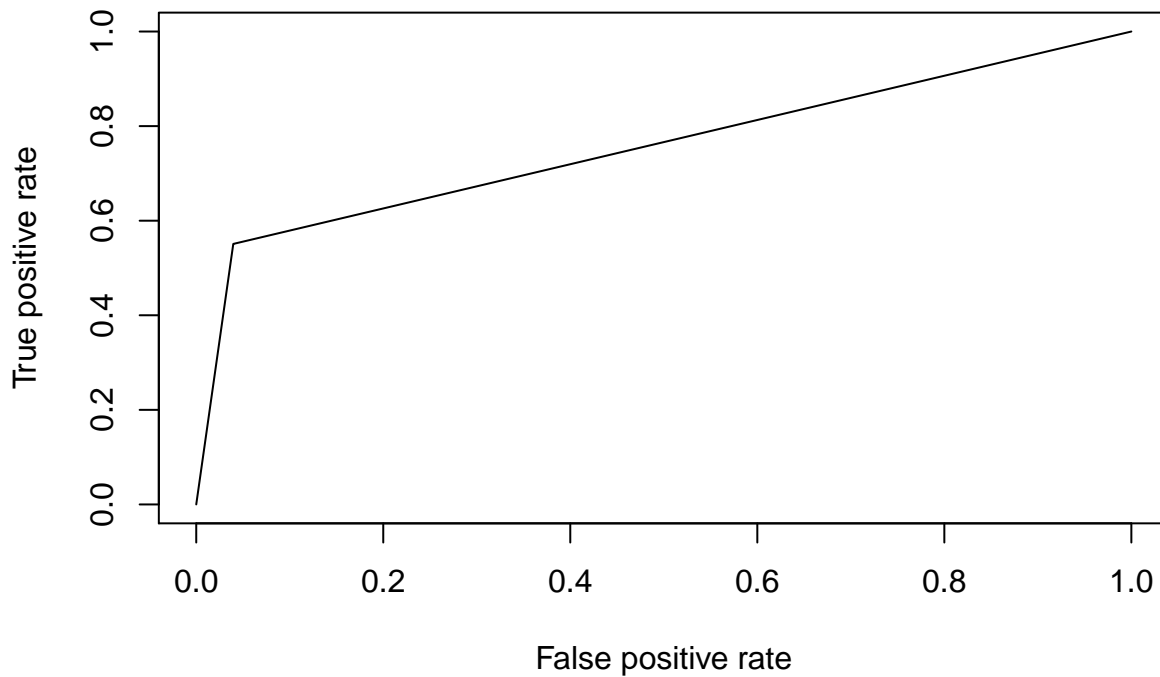
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no  yes
##          no 8775 521
##          yes 362 639
##
##           Accuracy : 0.9142
##           95% CI : (0.9087, 0.9196)
##       No Information Rate : 0.8873
##       P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.5438
##  McNemar's Test P-Value : 1.054e-07
##
##           Sensitivity : 0.55086
##           Specificity : 0.96038
##       Pos Pred Value : 0.63836
##       Neg Pred Value : 0.94395
##           Prevalence : 0.11265
##       Detection Rate : 0.06206
##   Detection Prevalence : 0.09721
##       Balanced Accuracy : 0.75562
##
##       'Positive' Class : yes
##

nn2_accuracy <- confusionMatrix(nnet_pred_2,test_data$y, positive = "yes")$overall[[1]]
nn2_accuracy <- nn2_accuracy*100
nn2_accuracy

## [1] 91.42469

# Plotting the ROC curve using the true and predicted values of target variable and
# computing area under the ROC curve
nnet_pred_fac_2 <- as.factor(nnet_pred_2)
pred_nn_2 <- prediction(predictions = as.numeric(nnet_pred_fac_2), labels = as.numeric(test_data$y))
perf_nn_2 <- performance(pred_nn_2,measure = "tpr", x.measure = "fpr")
plot(perf_nn_2, main="Neural Net 2")
```

Neural Net 2



```
perf.auc_nn_2 <- performance(pred_nn_2, measure = "auc")
nn2_auc <- unlist(perf.auc_nn_2@y.values)
nn2_auc
```

```
## [1] 0.7556215
```

```
### Support Vector Machine ###
```

```
library(kernlab)
```

```
##
## Attaching package: 'kernlab'
## The following object is masked from 'package:ggplot2':
##
##   alpha
```

```
# Building a SVM model using training set
```

```
set.seed(141)
svm_model <- ksvm(y~., data=train_data, kernel = "rbfdot", C=9)
svm_model
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc (classification)
## parameter : cost C = 9
##
## Gaussian Radial Basis kernel function.
## Hyperparameter : sigma = 0.055949851456535
##
## Number of Support Vectors : 6414
##
## Objective Function Value : -38609.8
## Training error : 0.051471
```

```
# Predicting the target variable by supplying test data for the model
svm_pred <- predict(svm_model, test_data[-21])
str(svm_pred)

## Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
# The accuracy of the SVM model is around 91% and a kappa value of 0.46
CrossTable(svm_pred, test_data$y)
```

```
##
##
##      Cell Contents
## |-----|
## |                      N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table: 10297
##
##
##      | test_data$y
##      svm_pred |      no |      yes | Row Total |
## -----|-----|-----|-----|
##      no |      8845 |      620 |      9465 |
##      |      23.713 |      186.780 |      |
##      |      0.934 |      0.066 |      0.919 |
##      |      0.968 |      0.534 |      |
##      |      0.859 |      0.060 |      |
## -----|-----|-----|-----|
##      yes |      292 |      540 |      832 |
##      |      269.763 |      2124.849 |      |
##      |      0.351 |      0.649 |      0.081 |
##      |      0.032 |      0.466 |      |
##      |      0.028 |      0.052 |      |
## -----|-----|-----|-----|
## Column Total |      9137 |      1160 |      10297 |
##      |      0.887 |      0.113 |      |
## -----|-----|-----|-----|
##
##
##
```

```
confusionMatrix(svm_pred, test_data$y, positive = "yes")
```

```
## Confusion Matrix and Statistics
##
##      Reference
## Prediction  no  yes
##      no  8845  620
##      yes  292  540
##
##      Accuracy : 0.9114
##      95% CI : (0.9058, 0.9168)
##      No Information Rate : 0.8873
##      P-Value [Acc > NIR] : 7.62e-16
```

```
##
##           Kappa : 0.4946
## McNemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.46552
##           Specificity : 0.96804
##           Pos Pred Value : 0.64904
##           Neg Pred Value : 0.93450
##           Prevalence : 0.11265
##           Detection Rate : 0.05244
##           Detection Prevalence : 0.08080
##           Balanced Accuracy : 0.71678
##
##           'Positive' Class : yes
##
```

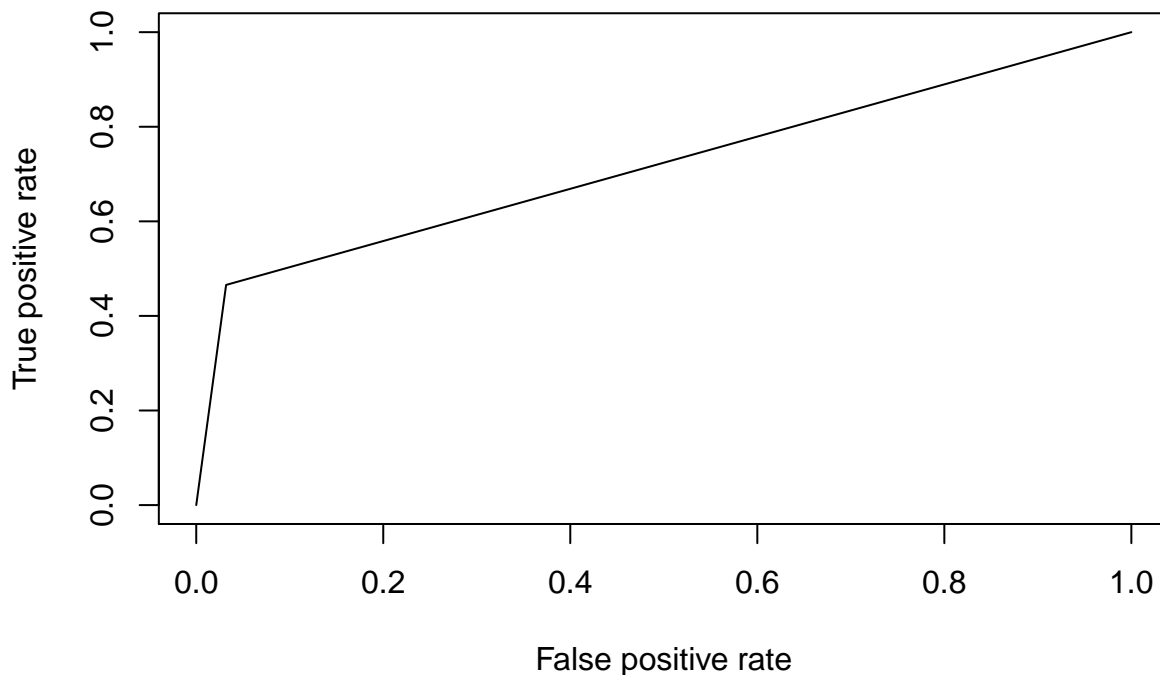
```
svm_accuracy <- confusionMatrix(svm_pred,test_data$y, positive = "yes")$overall[[1]]
svm_accuracy <- svm_accuracy*100
svm_accuracy
```

```
## [1] 91.14305
```

```
# ROC curve and AUC
```

```
pred_svm <- prediction(predictions = as.numeric(svm_pred), labels = as.numeric(test_data$y))
perf_svm <- performance(pred_svm,measure = "tpr", x.measure = "fpr")
plot(perf_svm, main="SVM")
```

SVM



```
perf.auc_svm <- performance(pred_svm, measure = "auc")
svm_auc <- unlist(perf.auc_svm@y.values)
svm_auc
```

```
## [1] 0.7167796
```

```

### Random Forest ###

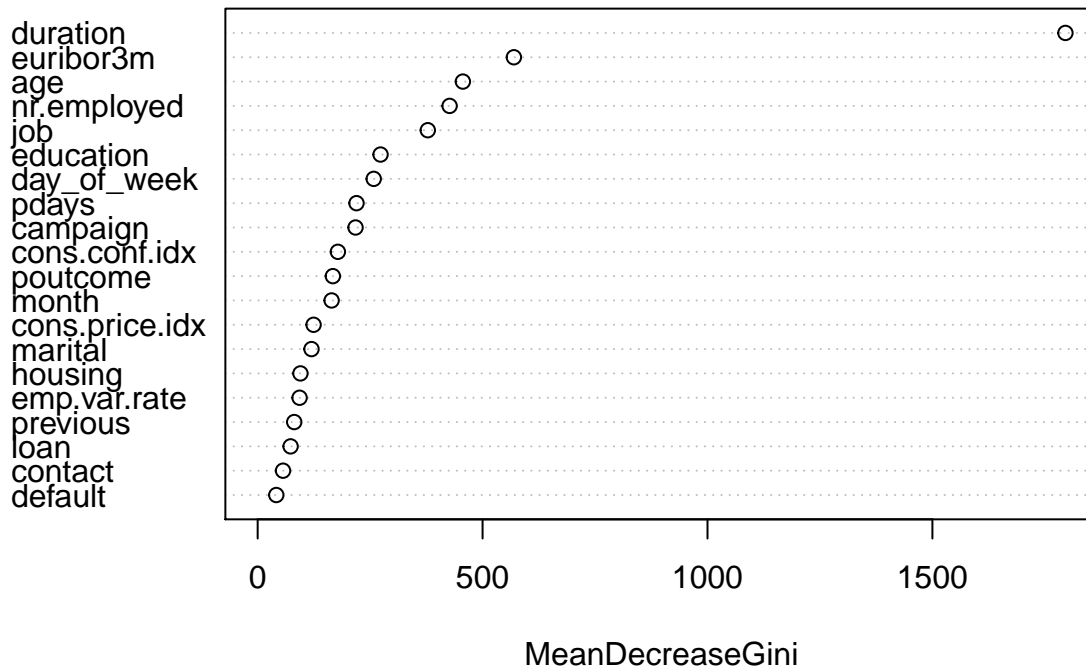
library(randomForest)

## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##     margin
# Building a random forest model using training data
set.seed(141)
rf_model <- randomForest(y~., ntree=80, data=train_data)
rf_model

##
## Call:
## randomForest(formula = y ~ ., data = train_data, ntree = 80)
##           Type of random forest: classification
##           Number of trees: 80
## No. of variables tried at each split: 4
##
##           OOB estimate of  error rate: 8.7%
## Confusion matrix:
##           no  yes class.error
## no  26371 1040  0.03794097
## yes  1648 1832  0.47356322
# Generating a variable importance graph using the random forest model we built. The
# variables with high Gini index are the most important variables. So, the variables
# at the top of the y-axis are more important in building a model than variables at
# the bottom
varImpPlot(rf_model,
           sort = T,
           n.var=20,
           main="Top 20 - Variable Importance")

```

Top 20 – Variable Importance



```
# Applying our model to test data for predicting the target variable y
rf_pred <- predict(rf_model, test_data[-21])
str(rf_pred)
```

```
## Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
## - attr(*, "names")= chr [1:10297] "1" "6" "10" "12" ...
```

```
# The accuracy of the model is around 91%
CrossTable(rf_pred, test_data$y)
```

```
##
##
## Cell Contents
## |-----|
## | N |
## | Chi-square contribution |
## | N / Row Total |
## | N / Col Total |
## | N / Table Total |
## |-----|
##
##
## Total Observations in Table: 10297
##
##
##      | test_data$y
## rf_pred | no | yes | Row Total |
## -----|----|-----|-----|
## no | 8810 | 547 | 9357 |
## | 30.972 | 243.956 | |
## | 0.942 | 0.058 | 0.909 |
## | 0.964 | 0.472 | |
## | 0.856 | 0.053 | |
```



```
## -----|-----|-----|-----|
##          yes |      327 |      613 |      940 |
##          |    308.301 |    2428.403 |      |
##          |      0.348 |      0.652 |    0.091 |
##          |      0.036 |      0.528 |      |
##          |      0.032 |      0.060 |      |
## -----|-----|-----|-----|
## Column Total |      9137 |      1160 |    10297 |
##          |      0.887 |      0.113 |      |
## -----|-----|-----|-----|
##
##
```

```
confusionMatrix(rf_pred,test_data$y, positive = "yes")
```

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

```
##
##          Reference
## Prediction  no  yes
##          no 8810 547
##          yes 327 613
##
##          Accuracy : 0.9151
##          95% CI : (0.9096, 0.9204)
##          No Information Rate : 0.8873
##          P-Value [Acc > NIR] : < 2.2e-16
##
##          Kappa : 0.5371
##          McNemar's Test P-Value : 1.284e-13
##
##          Sensitivity : 0.52845
##          Specificity : 0.96421
##          Pos Pred Value : 0.65213
##          Neg Pred Value : 0.94154
##          Prevalence : 0.11265
##          Detection Rate : 0.05953
##          Detection Prevalence : 0.09129
##          Balanced Accuracy : 0.74633
##
##          'Positive' Class : yes
##
```

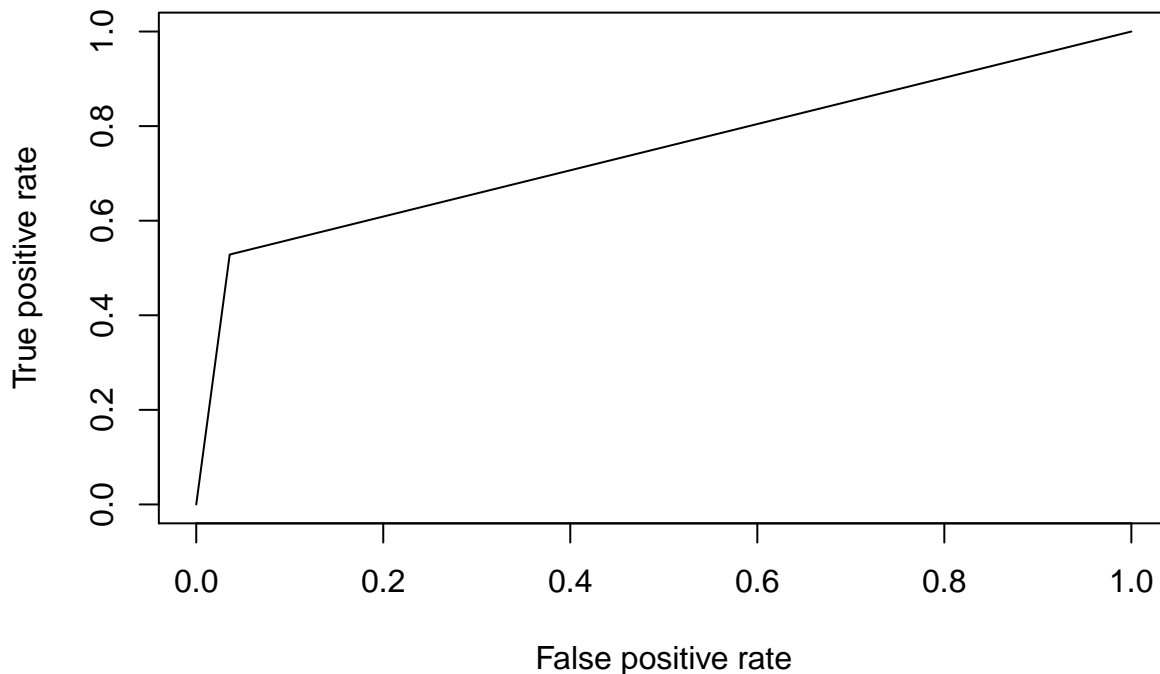
```
rf_accuracy <- confusionMatrix(rf_pred,test_data$y, positive = "yes")$overall[[1]]
rf_accuracy <- rf_accuracy*100
rf_accuracy
```

```
## [1] 91.51209
```

```
# ROC curve and AUC for the Random Forest model
```

```
pred_rf <- prediction(predictions = as.numeric(rf_pred), labels = as.numeric(test_data$y))
perf_rf <- performance(pred_rf,measure = "tpr", x.measure = "fpr")
plot(perf_rf, main="Random Forest")
```

Random Forest



```
perf.auc_rf <- performance(pred_rf, measure = "auc")
rf_auc <- unlist(perf.auc_rf@y.values)
rf_auc
```

```
## [1] 0.7463299
```

```
### Comparision of models ###
```

```
# Creating a matrix containing accuracy and AUC values of all the models
```

```
compare <- matrix(c(nb_accuracy, nb_auc, dt_accuracy, dt_auc, dt2_accuracy, dt2_auc,
                    nn_accuracy, nn_auc, nn2_accuracy, nn2_auc,
                    svm_accuracy, svm_auc, rf_accuracy, rf_auc),ncol=2, byrow = T)
```

```
compare <- as.data.frame(compare)
```

```
rownames(compare) <- c("NaiveBayes", "DecisionTree1", "DecisionTree2", "NeuralNetwork1",
                      "NeuralNetwork2", "SVM", "RandomForest")
```

```
names(compare) <- c("Accuracy", "AUC")
```

```
compare
```

```
##           Accuracy      AUC
## NaiveBayes    86.36496 0.7560870
## DecisionTree1 91.31786 0.7486222
## DecisionTree2 88.06448 0.8845781
## NeuralNetwork1 91.47324 0.7370795
## NeuralNetwork2 91.42469 0.7556215
## SVM           91.14305 0.7167796
## RandomForest  91.51209 0.7463299
```

```
# Adding a third column for the comparision matrix which serves as final evaluation metric
```

```
compare$evaluation <- (compare$Accuracy^2)*(compare$AUC)
compare
```

```
##              Accuracy      AUC evaluation
## NaiveBayes    86.36496 0.7560870 5639.582
## DecisionTree1 91.31786 0.7486222 6242.724
## DecisionTree2 88.06448 0.8845781 6860.215
## NeuralNetwork1 91.47324 0.7370795 6167.405
## NeuralNetwork2 91.42469 0.7556215 6315.842
## SVM          91.14305 0.7167796 5954.328
## RandomForest  91.51209 0.7463299 6250.112

### If FN and FP rates are considered significant in addition to the accuracy, we need to
# select the model with highest evaluation metric. The 2nd Decision Tree model is a clear
# standout in this case ###
compare[order(compare$evaluation, decreasing = T), ]

##              Accuracy      AUC evaluation
## DecisionTree2 88.06448 0.8845781 6860.215
## NeuralNetwork2 91.42469 0.7556215 6315.842
## RandomForest  91.51209 0.7463299 6250.112
## DecisionTree1 91.31786 0.7486222 6242.724
## NeuralNetwork1 91.47324 0.7370795 6167.405
## SVM          91.14305 0.7167796 5954.328
## NaiveBayes    86.36496 0.7560870 5639.582

### If model accuracy is the only metric to be considered, then we can select any of
# Random Forest, Neural network 1, Decision tree 1 or Support Vector Machines, as all
# these models have almost the same accuracy ###
compare[order(compare$Accuracy, decreasing = T), ]

##              Accuracy      AUC evaluation
## RandomForest  91.51209 0.7463299 6250.112
## NeuralNetwork1 91.47324 0.7370795 6167.405
## NeuralNetwork2 91.42469 0.7556215 6315.842
## DecisionTree1 91.31786 0.7486222 6242.724
## SVM          91.14305 0.7167796 5954.328
## DecisionTree2 88.06448 0.8845781 6860.215
## NaiveBayes    86.36496 0.7560870 5639.582

### K-fold cross validation ###

# Performing K-fold cross validation on the selected models to get a better estimation
# of its future performance

# Random Forest #
# 10-fold cross validation of the random forest model
set.seed(141)
folds <- createFolds(bank$y, k=10)
cv_results <- lapply(folds, function (x) {
  bank_train <- bank[-x, ]
  bank_test <- bank[x, ]
  bank_model <- randomForest(y~., ntree=80, data=bank_train)
  bank_predict <- predict(bank_model, bank_test[-21])
  accuracy <- confusionMatrix(bank_predict, bank_test$y, positive = "yes")$overall[[1]]
  accuracy <- accuracy*100
  return(accuracy)
})

# The average accuracy of our random forest models is 91.5% which is impressive
cv_rf <- mean(unlist(cv_results))
```

```
cv_rf
```

```
## [1] 91.55336
# Neural network #
# 10-fold cross validation of the Neural network 1 model #
set.seed(141)
folds <- createFolds(bank$y, k=10)
cv_results <- lapply(folds, function (x) {
  bank_train <- bank[-x, ]
  bank_test <- bank[x, ]
  bank_model <- nnet(y~age + job + marital + education +
                    default + housing + loan + contact +
                    month + day_of_week + duration + campaign +
                    pdays + previous + poutcome + emp.var.rate +
                    cons.price.idx + cons.conf.idx + euribor3m +
                    nr.employed,data=bank_train, size=9, decay=0.1)
  bank_predict <- predict(bank_model, bank_test[-21], type="class")
  accuracy <- confusionMatrix(bank_predict, bank_test$y, positive = "yes")$overall[[1]]
  accuracy <- accuracy*100
  return(accuracy)
})
```

```
## # weights:  496
## initial  value 22089.048723
## iter   10 value 10022.227098
## iter   20 value 8867.879442
## iter   30 value 7838.038323
## iter   40 value 7412.422302
## iter   50 value 7053.834068
## iter   60 value 6950.034387
## iter   70 value 6852.040777
## iter   80 value 6779.366270
## iter   90 value 6734.139892
## iter  100 value 6691.217632
## final  value 6691.217632
## stopped after 100 iterations
## # weights:  496
## initial  value 14851.744068
## iter   10 value 9530.122508
## iter   20 value 7591.611898
## iter   30 value 7108.830103
## iter   40 value 6868.484648
## iter   50 value 6758.667989
## iter   60 value 6666.797042
## iter   70 value 6619.283937
## iter   80 value 6574.173241
## iter   90 value 6516.668431
## iter  100 value 6469.026437
## final  value 6469.026437
## stopped after 100 iterations
## # weights:  496
## initial  value 21008.214412
## iter   10 value 9991.519945
## iter   20 value 8218.147097
## iter   30 value 7358.687938
## iter   40 value 7153.273406
```

```

## iter 50 value 6999.118583
## iter 60 value 6871.425526
## iter 70 value 6775.439317
## iter 80 value 6711.209502
## iter 90 value 6667.747996
## iter 100 value 6629.596193
## final value 6629.596193
## stopped after 100 iterations
## # weights: 496
## initial value 20710.977832
## iter 10 value 9913.273557
## iter 20 value 8084.479475
## iter 30 value 7515.789067
## iter 40 value 7184.729051
## iter 50 value 6996.784704
## iter 60 value 6860.558637
## iter 70 value 6775.431046
## iter 80 value 6707.920893
## iter 90 value 6657.175065
## iter 100 value 6603.203579
## final value 6603.203579
## stopped after 100 iterations
## # weights: 496
## initial value 21505.172399
## iter 10 value 9871.647541
## iter 20 value 9040.838701
## iter 30 value 8223.511222
## iter 40 value 7649.727016
## iter 50 value 7312.263282
## iter 60 value 7170.727621
## iter 70 value 6983.606220
## iter 80 value 6876.192534
## iter 90 value 6807.789574
## iter 100 value 6756.335308
## final value 6756.335308
## stopped after 100 iterations
## # weights: 496
## initial value 23453.238456
## iter 10 value 10682.643341
## iter 20 value 9807.973937
## iter 30 value 8632.047387
## iter 40 value 8145.555106
## iter 50 value 7854.271070
## iter 60 value 7594.317945
## iter 70 value 7391.997000
## iter 80 value 7210.124825
## iter 90 value 7091.610037
## iter 100 value 7022.800105
## final value 7022.800105
## stopped after 100 iterations
## # weights: 496
## initial value 32134.744969
## iter 10 value 10701.027253
## iter 20 value 8258.479608
## iter 30 value 7486.135774
## iter 40 value 7339.871893

```

```

## iter 50 value 7245.080537
## iter 60 value 7061.461826
## iter 70 value 6922.190655
## iter 80 value 6810.266255
## iter 90 value 6724.143673
## iter 100 value 6665.325276
## final value 6665.325276
## stopped after 100 iterations
## # weights: 496
## initial value 38251.920488
## iter 10 value 10791.902372
## iter 20 value 8741.588341
## iter 30 value 7981.429351
## iter 40 value 7620.417152
## iter 50 value 7281.177400
## iter 60 value 7086.904004
## iter 70 value 6967.582628
## iter 80 value 6882.093157
## iter 90 value 6752.317339
## iter 100 value 6656.112322
## final value 6656.112322
## stopped after 100 iterations
## # weights: 496
## initial value 20609.319365
## iter 10 value 10144.478051
## iter 20 value 7840.238306
## iter 30 value 7261.513898
## iter 40 value 7114.246439
## iter 50 value 6969.709706
## iter 60 value 6855.065447
## iter 70 value 6804.080225
## iter 80 value 6744.642738
## iter 90 value 6667.198924
## iter 100 value 6604.121202
## final value 6604.121202
## stopped after 100 iterations
## # weights: 496
## initial value 74174.998010
## iter 10 value 10115.236609
## iter 20 value 7694.136562
## iter 30 value 7404.824948
## iter 40 value 7200.070132
## iter 50 value 7058.566793
## iter 60 value 6887.861754
## iter 70 value 6781.302972
## iter 80 value 6702.055970
## iter 90 value 6652.224646
## iter 100 value 6616.154756
## final value 6616.154756
## stopped after 100 iterations
# The average accuracy of the neural network model is 91.3%
cv_nn <- mean(unlist(cv_results))
cv_nn

```

```
## [1] 91.34698
```

```

# Decision tree #
# 10-fold cross validation of the Decision tree 1 model
set.seed(141)
folds <- createFolds(bank$y, k=10)
cv_results <- lapply(folds, function (x) {
  bank_train <- bank[-x, ]
  bank_test <- bank[x, ]
  bank_model <- C5.0(bank_train[-21], bank_train$y, trails=20)
  bank_predict <- predict(bank_model, bank_test[-21], type="class")
  accuracy <- confusionMatrix(bank_predict, bank_test$y, positive = "yes")$overall[[1]]
  accuracy <- accuracy*100
  return(accuracy)
})

# The decision tree model has an average accuracy of 91.3%
cv_dt <- mean(unlist(cv_results))
cv_dt

```

```
## [1] 91.32757
```

```

#
set.seed(141)
folds <- createFolds(bank$y, k=10)
cv_results <- lapply(folds, function (x) {
  bank_train <- bank[-x, ]
  bank_test <- bank[x, ]
  bank_model <- ksvm(y~., data=bank_train, kernel = "rbfdot", C=9)
  bank_predict <- predict(bank_model, bank_test[-21])
  accuracy <- confusionMatrix(bank_predict, bank_test$y, positive = "yes")$overall[[1]]
  accuracy <- accuracy*100
  return(accuracy)
})

# The SVM model has an average accuracy of 90.9%
cv_svm <- mean(unlist(cv_results))
cv_svm

```

```
## [1] 90.96581
```

```

### Random forest model is more robust and stable in predicting future outcomes and it is
# the best model to use if accuracy is the only criterion ###

```