Bank Marketing

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Introduction

This project applies machine learning technique that go beyond standard linear regression. I had the prospect to use a publicly available dataset to resolve the trouble of my alternative. I sifted through the datasets available on Kaggle and chose a finance/bank related dataset. I work at a bank so I was geared in the direction of selecting a topic that's applicable to the banking industry.

The aim of the project is to answer the following question:

What type of behaviors do possible customers show that result in them extra likely to subscribe to a term deposit?

The industry difficulty is to devise a objective marketing strategy for the bank base on the behavioral data collected. The dataset is included in one of the obedience files and can be downloaded from Kaggle (https://www.kaggle.com/henriqueyamahata/bank-marketing).

The Dataset: It contain 41,188 customer data on direct advertising campaign (phone calls) of a Portuguese banking organization.

It has the following variables:

Client: age, job, default status, housing, marital, education, and loan

Campaign: last contact day of the week, last contact type, last contact, last contact duration and month of year

Others: number of contacts performed in current campaign, number of days that passed by after the client was last contacted, number of contacts performed before this campaign, outcome of previous campaign, and whether a client has subscribed a term deposit

Key Steps Performed:

.

I first used Data Classification to examine the set related with direct marketing campaigns of a Portuguese banking institution. The objective of the classification is to predict if the client will subscribe to a Term Deposit. Data Classification is the use of machine learning techniques to organize datasets into related sub-populations, not previous specified in the dataset. This can uncover hidden characteristics within data, and identify hidden categories that new data belongs within. The rest of the key steps that were performed used the data science techniques of Exploratory Data Analysis, Data Classification with the help of K-Nearest Neighbor(k-NN).

1. Data Analysis

Exploratory Analysis

Loading the required packages:

```
rm(list = ls())
options(warn=-1)

if(!require(readr)) install.packages("readr", repos = "")
if(!require(tidyverse)) install.packages("tidyverse", repos = "")
if(!require(GGally)) install.packages("GGally", repos = "")
if(!require(glmnet)) install.packages("glmnet", repos = "")
if(!require(Matrix)) install.packages("Matrix", repos = "")
if(!require(DataExplorer)) install.packages("DataExplorer", repos = "")
if(!require(corrplot)) install.packages("corrplot", repos = "")
if(!require(caret)) install.packages("caret", repos = "")
if(!require(randomForest)) install.packages("randomForest", repos = "")
if(!require(class)) install.packages("class", repos = "")
if(!require(gmodels)) install.packages("gmodels", repos = "")
if(!require(dplyr)) install.packages("dplyr", repos = "")
if(!require(psych)) install.packages("psych", repos =  "")
library(readr)
library(tidyverse)
library(GGally)
library(glmnet)
library(Matrix)
library(ggplot2)
library(DataExplorer)
library(corrplot)
library(caret)
library(randomForest)
library(class)
library(gmodels)
library(dplyr)
library(psych)
set.seed(1)
```

Loading the dataset:

```
#setwd("C:/Users/1012233/Downloads/20191103 - R Studio Kaggle project")
#data.df <- read.csv("bank-additional-full.csv", header=TRUE, sep=";")
```

Viewing the column names of the dataset:

```
names(data.df)

##  [1]  "age"              "job"            "marital"         "education"
##  [5] "default"          "housing"        "loan"            "contact"
##  [9] "month"            "day_of_week"    "duration"        "campaign"
## [13] "pdays"            "previous"       "poutcome"        "emp.var.rate"
## [17] "cons.price.idx" "cons.conf.idx"    "euribor3m"       "nr.employed"
## [21] "y"
```

Column details of the dataset:

```
str(data.df)

## '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 -3
6.4 -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 ...
```

Summary analysis of the dataset:

```
summary(data.df)

##         age                  job               marital
##   Min.    :17.00    admin.     :10422    divorced: 4612
##   1st Qu.:32.00   blue-collar: 9254   married  :24928
## Median :38.00 technician : 6743 single  :11568
##   Mean    :40.02    services    :  3969     unknown  :     80
## 3rd Qu.:47.00 management : 2924
##   Max.    :98.00    retired       : 1720
##                     (Other)       : 6156
##                  education            default              housing
##   university.degree       :12168     no        :32588     no         18622
##   high.school             :  9515    unknown: 8597     unknown:  990
##   basic.9y                : 6045     yes     :       3     yes      21576
##   professional.course: 5243
##   basic.4y                : 4176
##   basic.6y                : 2292
##   (Other)                 : 1749
##         loan              contact              month         day_of_week
##   no       :33950    cellular :26144    may      :13769    fri:7827
##   unknown:  990     telephone:15044    jul       :  7174    mon:8514
##   yes      :  6248                      aug       :  6178    thu:8623
##                                          jun       : 5318    tue:8090
##                                          nov       :  4101    wed:8134
##                                          apr       :  2632
##                                          (Other):   2016
##      duration          campaign             pdays            previous
##   Min.     :      0.0    Min.      :  1.000    Min.:    0.0Min.    :0.000
##   1st  Qu.:  102.0    1st  Qu.:  1.000    1st  Qu.:999.0    1st  Qu.:0.000
##   Median  :  180.0    Median  :  2.000    Median  :999.0    Median  :0.000
##    Mean     :  258.3   Mean      :  2.568   Mean      :962.5    Mean       :0.173
##   3rd   Qu.:   319.0    3rd   Qu.:   3.000    3rd   Qu.:999.0    3rd   Qu.:0.000
##    Max.     :4918.0    Max.     :56.000     Max.      :999.0     Max.       :7.000
##
##            poutcome          emp.var.rate        cons.price.idx     cons.conf.idx
##   failure  : 4252          Min.      :-3.40000    Min.      :92.20     Min.      :-50.8
##   nonexistent:35563     1st Qu.:-1.80000    1st Qu.:93.08     1st Qu.:-42.7
##   success      : 1373    Median : 1.10000    Median :93.75     Median  :-41.8
##                            Mean      : 0.08189    Mean      :93.58     Mean      :-40.5
##                            3rd  Qu.: 1.40000    3rd  Qu.:93.99     3rd  Qu.:-36.4
##                            Max.      : 1.40000    Max.      :94.77     Max.      :-26.9
##
##      euribor3m          nr.employed        y
##   Min.     :0.634     Min.     :4964     no  :36548
##  1st Qu.:1.344   1st  Qu.:5099   yes:  4640
##  Median :4.857   Median  :5191
##  Mean   :3.621   Mean    :5167
##  3rd Qu.:4.961   3rd  Qu.:5228
##  Max.   :5.045   Max.    :5228
##
```

Data Preparation

We check if there are any missing values that exists:

```
sum(is.na(data.df))

## [1] 0
```

There are no missing values in our dataset.

In the above investigative analysis, we experimental that there are many variables with class=int; hence, we change them keen on numeric class

Converting quantitative values to numeric class:

```
data.df$age <- as.numeric(data.df$age)
data.df$duration <- as.numeric(data.df$duration)
data.df$campaign <- as.numeric(data.df$campaign)
data.df$pdays <- as.numeric(data.df$pdays)
data.df$previous <- as.numeric(data.df$previous)
```

Ordering the levels of month:

```
data.df$month<- factor(data.df$month, ordered = TRUE, levels = c("mar", "apr"
, "may", "jun", "jul", "aug", "sep", "oct", "nov", "dec"))
```

Since the target variable is a categorical variables with 2 possible values: yes, no; we transform it into a numerical denotation: 1,0 respectively.

Transforming the target variable as Yes=1 and No=0:

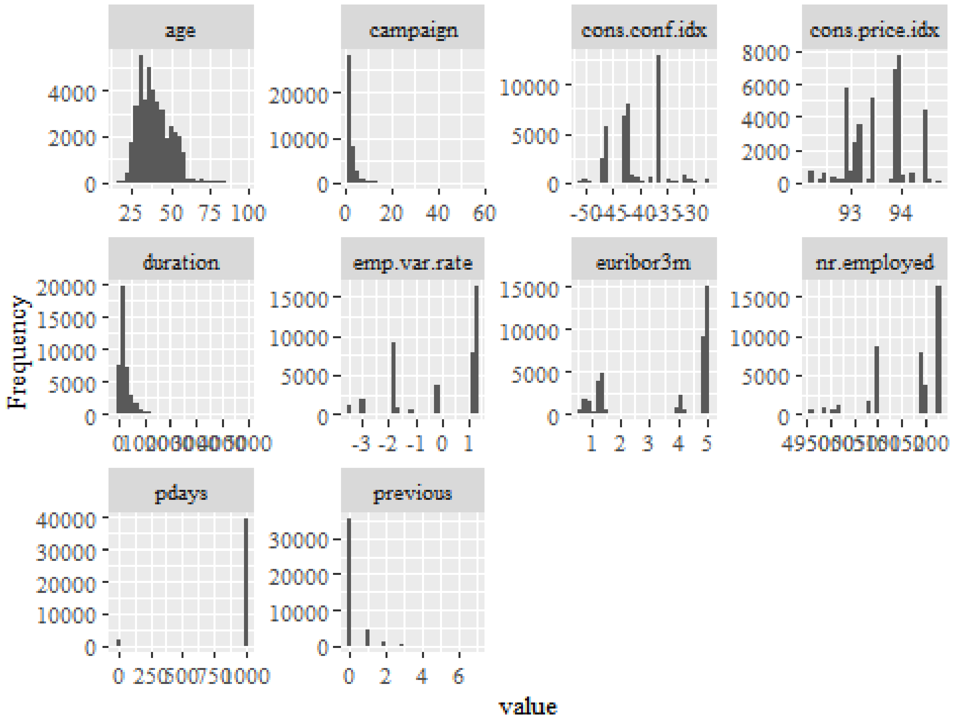
```
table(data.df$y)

##
##    no   yes
## 36548  4640

data.df <- data.df %>%
  mutate(y = ifelse(y=="yes", 1, 0))

data.df$y <- as.factor(data.df$y)
table(data.df$y)
```

```
##
##      0      1
##  36548   4640
```

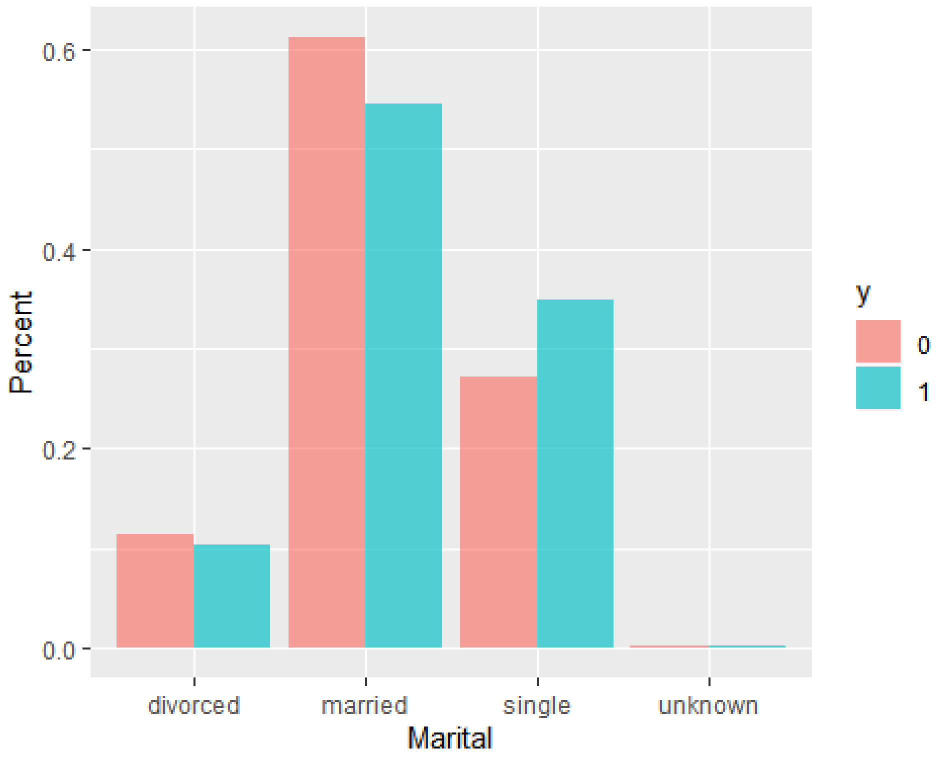
Descriptive Analysis

Let us look at the histogram of the input variables:

```
plot_histogram(data.df[,-21],ggtheme = theme_gray(base_size = 10, base_family
= "serif"))
```

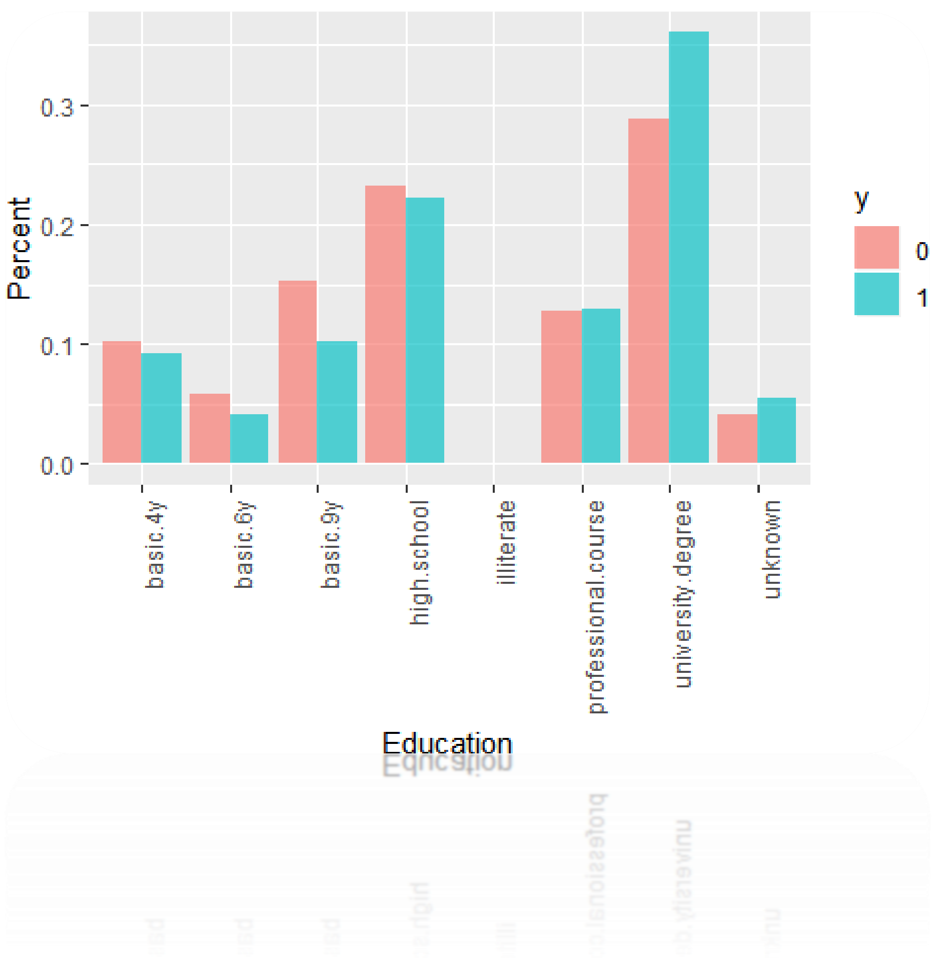


```
mytable <- table(data.df$marital, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("marital", "y", "perc")
ggplot(data = tab, aes(x = marital, y = perc, fill = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Marital")+ylab("Percent")
```



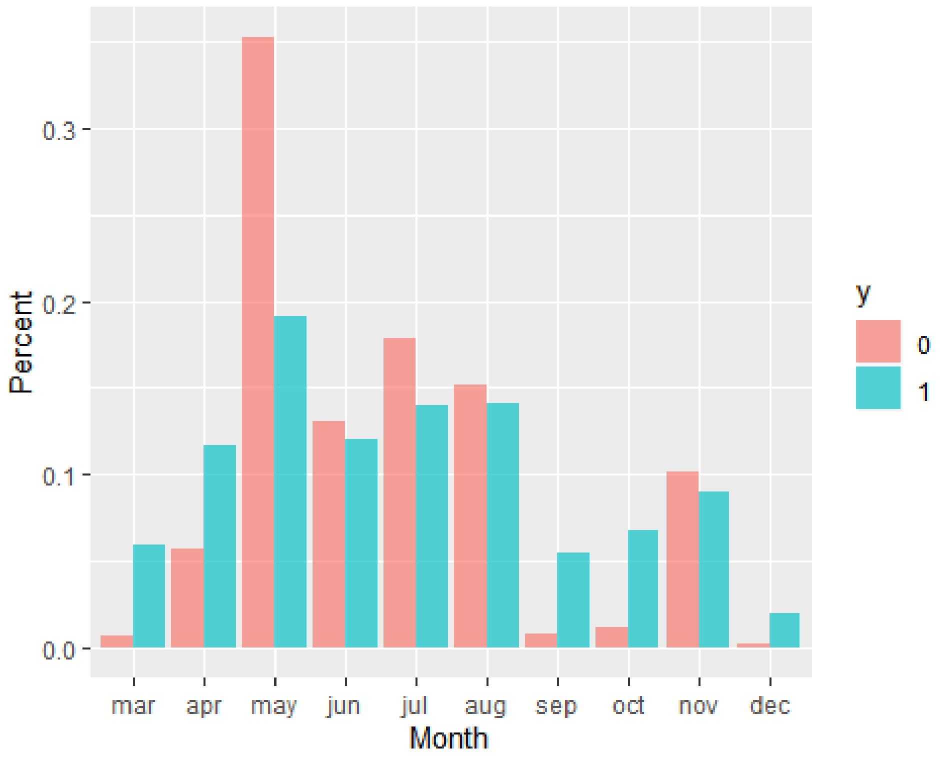
With deference to Marital Status there is not an experiential large difference in the quantity of people subscribe to term deposit and people without term deposits.

```
mytable <- table(data.df$education, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("education", "y", "perc")
ggplot(data = tab, aes(x = education, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
theme(axis.text.x=element_text(angle=90,hjust=1)) +
  xlab("Education")+ylab("Percent")
```



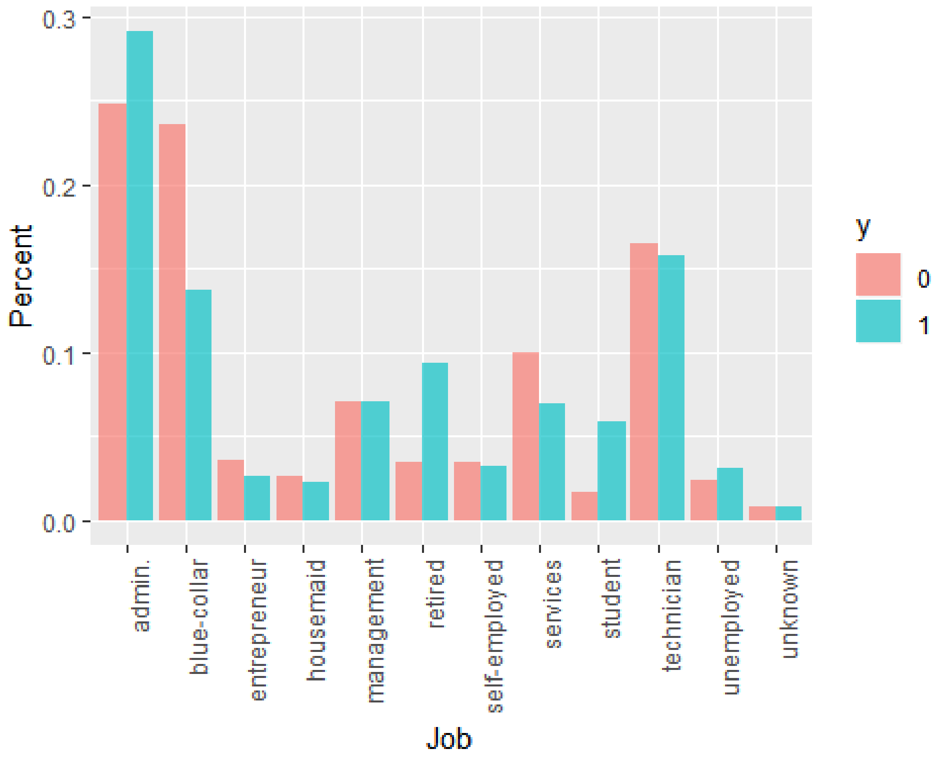
We can observe that customers who sign up for bank deposits, proportionally, have achieve a higher level of education, than those who didn't sign up.

```
mytable <- table(data.df$month, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-   c("month", "y", "perc")
ggplot(data = tab, aes(x = month, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Month")+ylab("Percent")
```

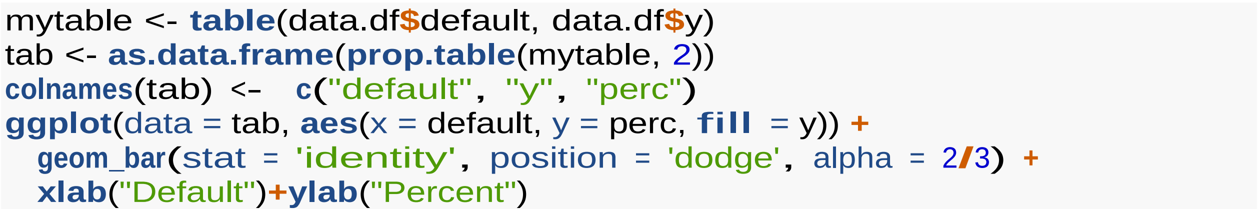


The month of May is when the maximum number of calls were located for marketing deposits. The months of April, September, October, and December is the time when a higher proportion of populace subscribed for expression deposits.

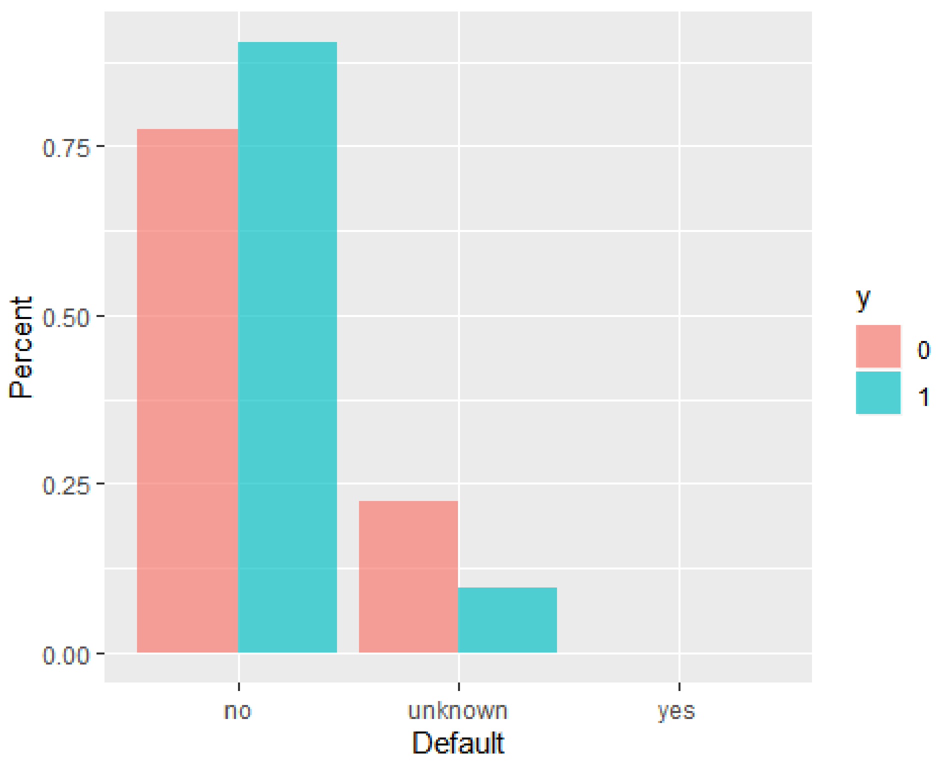
```
mytable <- table(data.df$job,  data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-   c("job", "y", "perc")
ggplot(data = tab, aes(x = job, y = perc, fill  = y)) + geom_bar(stat
  = 'identity', position  = 'dodge', alpha  = 2/3) +
theme(axis.text.x=element_text(angle=90,hjust=1)) +
  xlab("Job")+ylab("Percent")
```



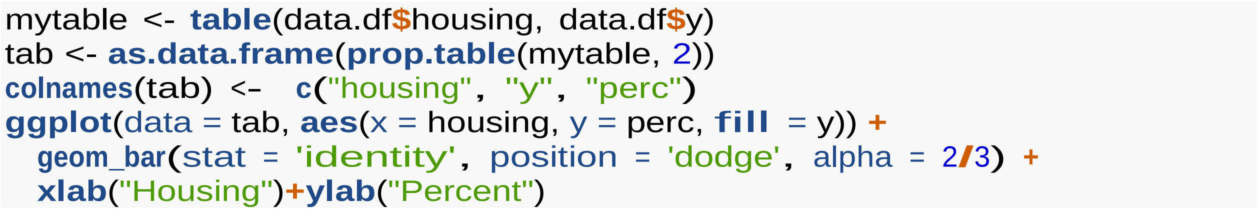
We see there are higher size for customers sign up for the term deposits who have the job of admin, retired, and students.



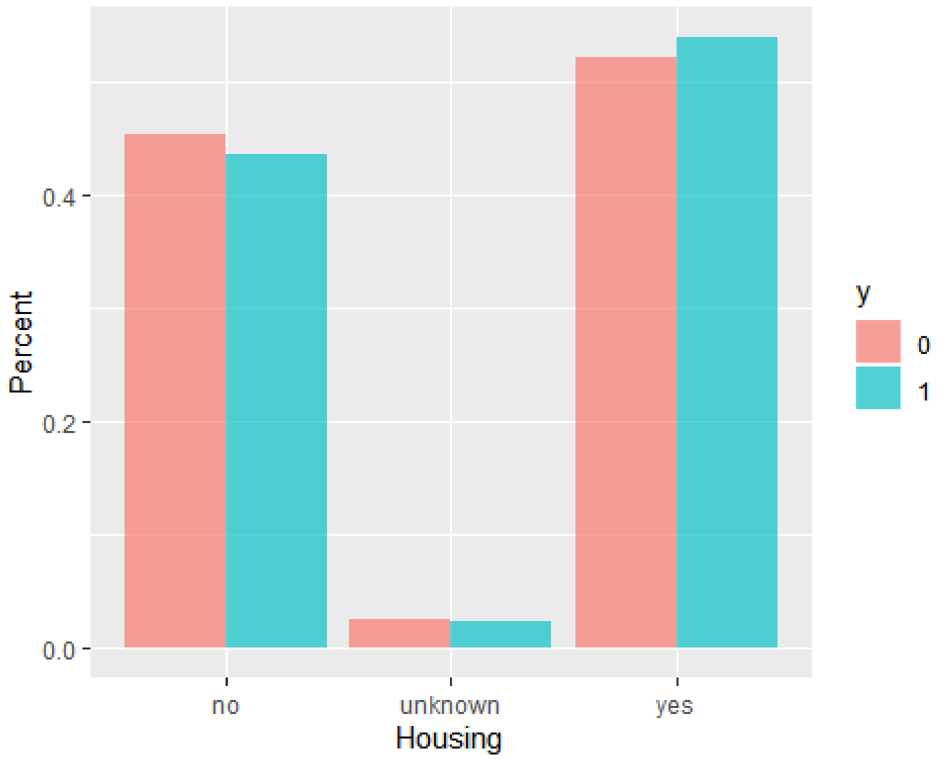
```
mytable <- table(data.df$default, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("default", "y", "perc")
ggplot(data = tab, aes(x = default, y = perc, fill = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Default")+ylab("Percent")
```



The data show that people who aren't in default are a higher proportion of people who have subscribed for bank deposits.

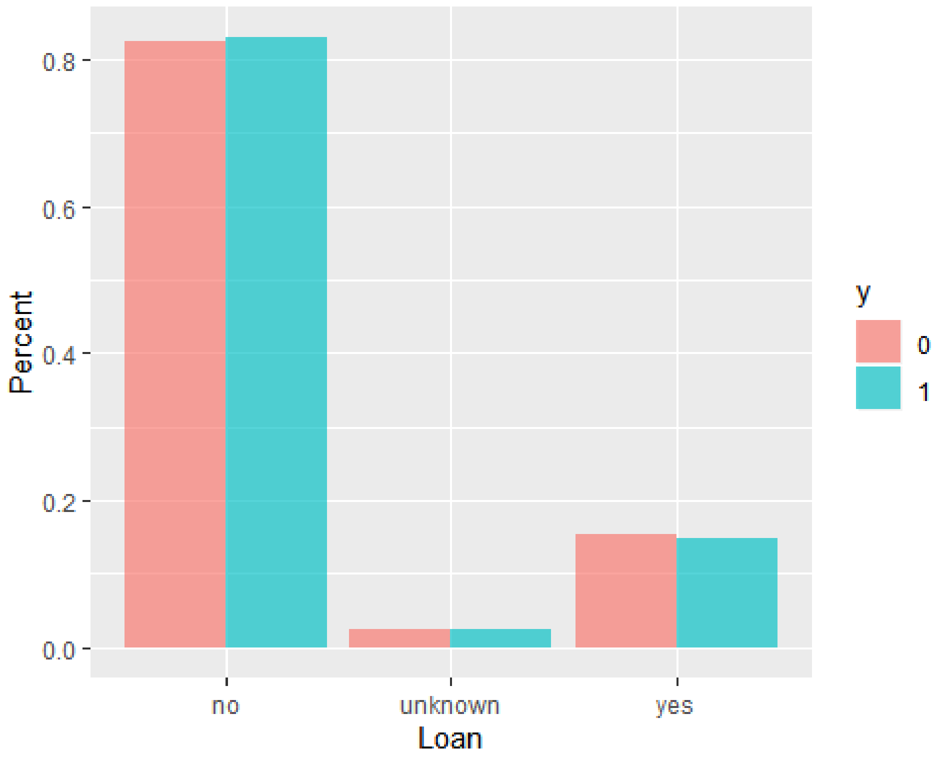


```
mytable <- table(data.df$housing, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("housing", "y", "perc")
ggplot(data = tab, aes(x = housing, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Housing")+ylab("Percent")
```

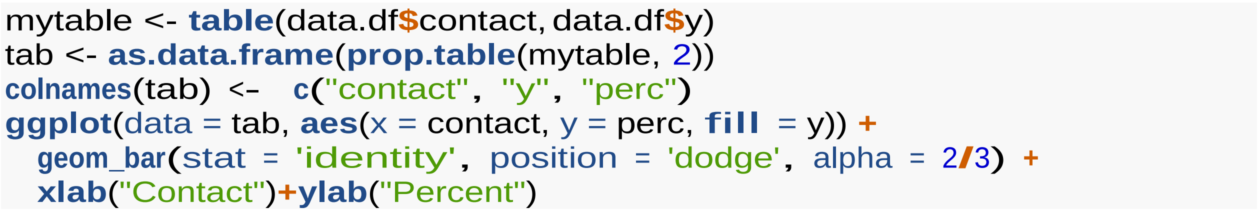


We see that a high amount of people who have subscribe for bank deposit are home owner versus ones that don't hold their own houses.

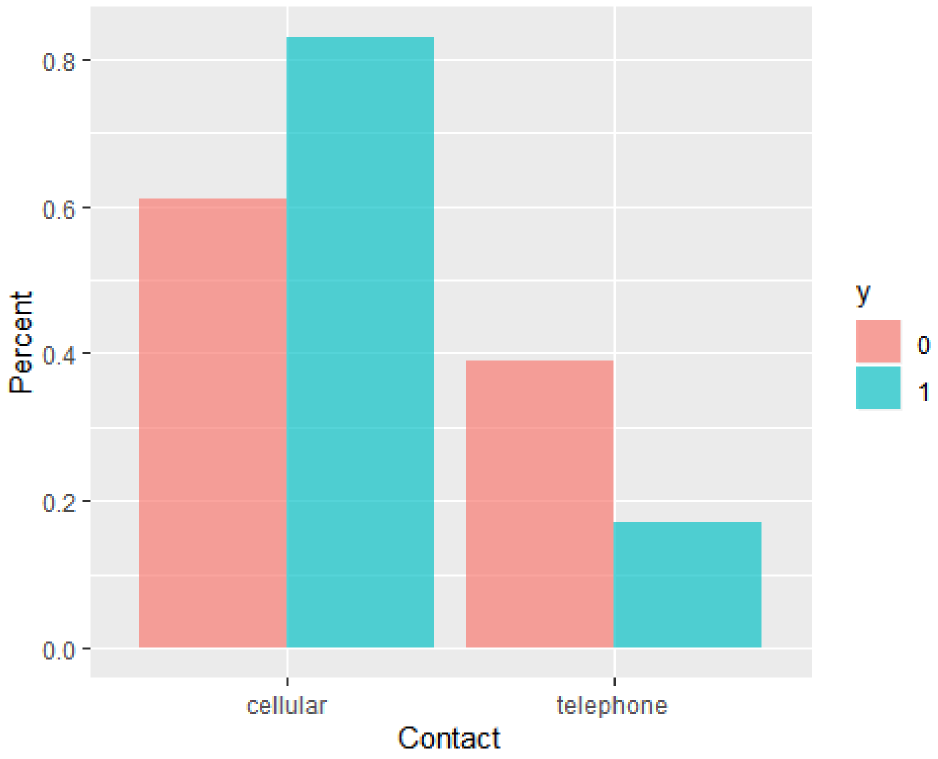
```
mytable <- table(data.df$loan, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <- c("loan", "y", "perc")
ggplot(data = tab, aes(x = loan, y = perc, fill = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Loan")+ylab("Percent")
```



We see the section of people who have subscribe and not subscribe to a term deposit is the identical for categories of the Loan.

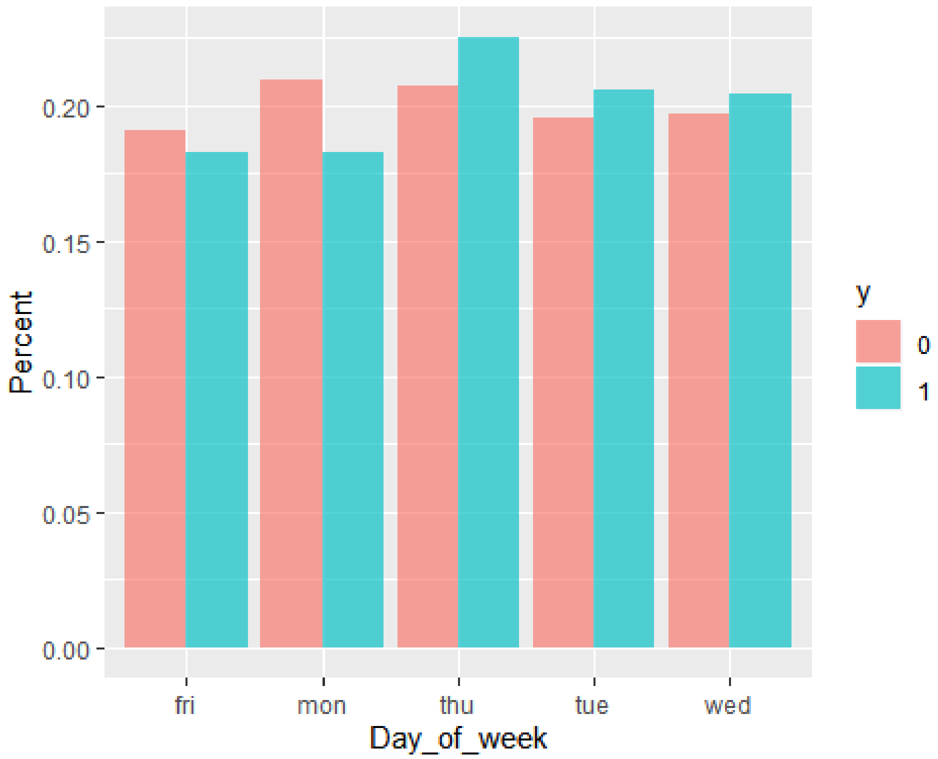


```
mytable <- table(data.df$contact, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("contact", "y", "perc")
ggplot(data = tab, aes(x = contact, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Contact")+ylab("Percent")
```



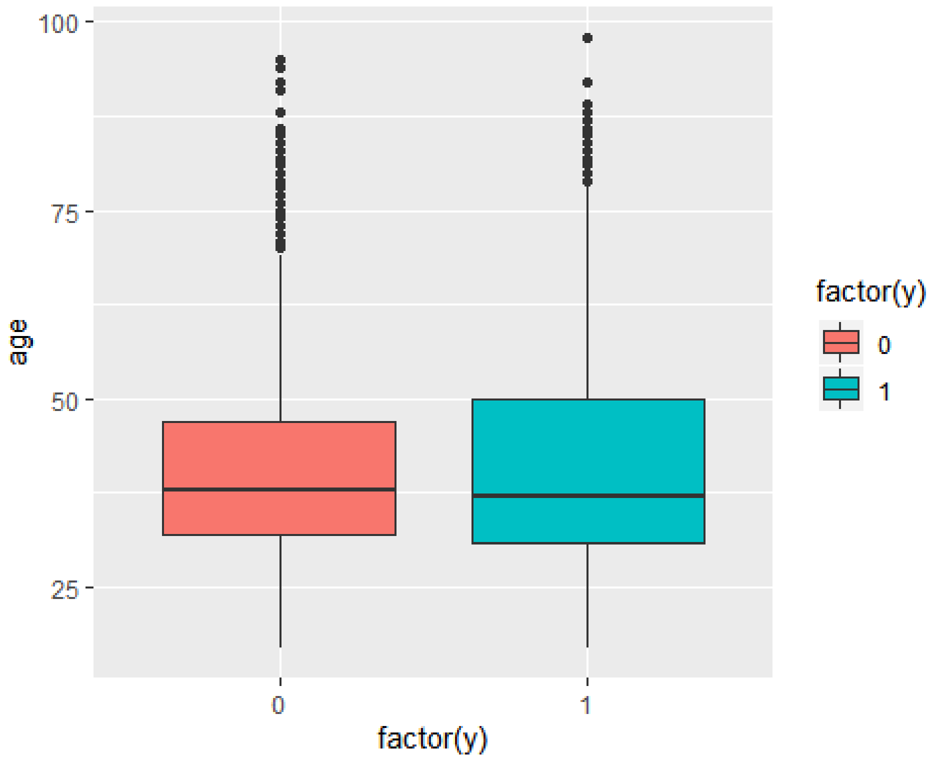
Customers who have cell phones, and therefore a more direct way of communicate, signed up for period deposits more than those who just had a landline telephone.

```
mytable <- table(data.df$day_of_week,data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-   c("day_of_week", "y", "perc")
ggplot(data = tab, aes(x = day_of_week, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Day_of_week")+ylab("Percent")
```



campaign that were perform midweek, on Tuesdays, Wednesdays, and Thursdays had a somewhat higher section of people who subscribe for bank deposit.

```
mytable <- table(data.df$poutcome, data.df$y)
tab <- as.data.frame(prop.table(mytable, 2))
colnames(tab) <-  c("poutcome", "y", "perc")
ggplot(data = tab, aes(x = poutcome, y = perc, fill  = y)) +
  geom_bar(stat = 'identity', position = 'dodge', alpha = 2/3) +
  xlab("Outcome of previous marketing  campaign")+ylab("Percent")
```



The age variety for successful exchange has a slightly lower median, but higher quartile ranges.

```
df_cor <- select_if(data.df, is.numeric) %>% cor()
corrplot(df_cor, method = "number")
```

2. Results ()

Data Preparation

Includes Data Modeling and performance missing values for period were clean out because if duration=0 then y="no" (no call was made). Thus, it doesn't make logic to have 0 second duration. I also filtered out education uneducated, and default yes since they only have 1 surveillance each. We can't predict these circumstances if they happen to be in the examination data but not the train data.

```
data.df <- data.df %>%
  filter(duration != 0, education != "illiterate", default != "yes") %>%
  mutate(y = ifelse(y==1, 1, 0))
```

Split the data into training and test datasets:

```
set.seed(123)
trainIndex <- createDataPartition(data.df$y,
                                  p = 0.8, # training contains 80% of data
                                  list = FALSE)
dfTrain <- data.df[ trainIndex,]
dfTest  <-  data.df[-trainIndex,]

dim(dfTrain)

## [1] 32931      21

dim(dfTest)

## [1] 8232    21
```

The code and output above show that the train Data dataset has 8929 rows and 17 columns and the test Data dataset gas 2233 rows and 17 columns. The number of columns remains the same because the dataset was split up and down.

Data Modeling using KNN

We will make a copy of our data set so that we can prepare it for our K-NN classification.

```
data_knn <- data.df

str(data_knn)

## 'data.frame':     41163 obs. of 21 variables:
## $ age            : num 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          : Ord.factor w/ 10 levels "mar"<"apr"<"may"<..: 3 3 3 3 3
3 3 3 3 3 ...
## $ day_of_week    : Factor w/ 5 levels "fri","mon","thu",..: 2 2 2 2 2 2 2
2 2 2 ...
## $ duration       : num 261 149 226 151 307 198 139 217 380 50 ...
## $ campaign       : num 1 1 1 1 1 1 1 1 1 1 ...
## $ pdays          : num 999 999 999 999 999 999 999 999 999 999 ...
## $ 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 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 -3
6.4 -36.4 ...
## $ euribor3m      : num 4.86 4.86 4.86 4.86 4.86 ...
## $ nr.employed    : num 5191 5191 5191 5191 5191 ...
## $ y              : num 0 0 0 0 0 0 0 0 0 0 ...
```

Because K-NN algorithm involve influential distances between data points, we have to use numeric variables only. This is relevant only to independent variables. The objective variable for k-NN categorization should remain a factor changeable. First, we scale the data just in case our features are on different metrics. For example, if we had “duration” as a variable, it would be on a much better scale than “age”, which might be problematic given the k-NN relies on distance. Note that we are using the ‘scale’ function here, which income we are scaling to a z-score metric.

We see that the variables “age”, “duration”, “campaign”, “pdays”, “previous”, “emp.var.rate”, “cons.price.idx”, “cons.conf.idx”, “euribor3m” and “nr.employed” are interger variables, which means they can be scaled.

```
data_knn[, c("age", "duration", "campaign", "pdays", "previous", "emp.var.rat
e", "cons.price.idx", "cons.conf.idx", "euribor3m","nr.employed")] <- scale(d
ata_knn[, c("age", "duration", "campaign", "pdays", "previous", "emp.var.rate
", "cons.price.idx", "cons.conf.idx",  "euribor3m","nr.employed")])

head(data_knn)
```

```
##             age       job marital   education default housing loan
## 1   1.533684728 housemaid married    basic.4y      no      no   no
## 2   1.629657912  services married high.school unknown      no   no
## 3  -0.289805768  services married high.school      no     yes   no
## 4  -0.001886216    admin. married    basic.6y      no      no   no
## 5   1.533684728  services married high.school      no      no  yes
## 6   0.477979704  services married    basic.9y unknown      no   no
##      contact month day_of_week    duration   campaign     pdays   previous
## 1  telephone   may         mon  0.01036255 -0.5658418 0.1954061 -0.3494959
## 2  telephone   may         mon -0.42162181 -0.5658418 0.1954061 -0.3494959
## 3  telephone   may         mon -0.12463256 -0.5658418 0.1954061 -0.3494959
## 4  telephone   may         mon -0.41390781 -0.5658418 0.1954061 -0.3494959
## 5  telephone   may         mon  0.18778470 -0.5658418 0.1954061 -0.3494959
## 6  telephone   may         mon -0.23262865 -0.5658418 0.1954061 -0.3494959
##       poutcome emp.var.rate cons.price.idx cons.conf.idx euribor3m
## 1  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
## 2  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
## 3  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
## 4  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
## 5  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
## 6  nonexistent    0.6480509      0.7224735     0.8865513 0.7124339
##    nr.employed y
## 1    0.3317071 0
## 2    0.3317071 0
## 3    0.3317071 0
## 4    0.3317071 0
## 5    0.3317071 0
## 6    0.3317071 0
```

```
str(data_knn)
```

```
## 'data.frame':     41163 obs. of  21 variables:
##  $ age           : num  1.53368 1.62966 -0.28981 -0.00189 1.53368 ...
##  $ 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         : Ord.factor w/ 10 levels "mar"<"apr"<"may"<..: 3 3 3 3 3
3 3 3 3 3 ...
##  $ day_of_week   : Factor w/ 5 levels "fri","mon","thu",..: 2 2 2 2 2 2 2
2 2 2 ...
##  $ duration      : num  0.0104 -0.4216 -0.1246 -0.4139 0.1878 ...
##  $ campaign      : num  -0.566 -0.566 -0.566 -0.566 -0.566 ...
##  $ emp.var.rate  : num  0.648 0.648 0.648 0.648 0.648 ...
##  $ cons.price.idx: num  0.722 0.722 0.722 0.722 0.722 ...
##  $ cons.conf.idx : num  0.887 0.887 0.887 0.887 0.887 ...
##  $ euribor3m     : num  0.712 0.712 0.712 0.712 0.712 ...
##  $ nr.employed   : num  0.332 0.332 0.332 0.332 0.332 ...
##  $ y             : num  0 0 0 0 0 0 0 0 0 0 ...
```

We can observe that the variables “job”, “marital”, “education”, “default”, “housing”, “loan”, “contact”, “month”, “day_of_week” and “poutcome” are thing variables that have two or more levels.

** Then dummy code variables that have two levels, but are not numeric. **

```
data_knn$contact <- dummy.code(data_knn$contact)
```

Next we dummy code variables that have three or more levels.

```
job <- as.data.frame(dummy.code(data_knn$job))
marital <- as.data.frame(dummy.code(data_knn$marital))
education <- as.data.frame(dummy.code(data_knn$education))
default <- as.data.frame(dummy.code(data_knn$default))
housing <- as.data.frame(dummy.code(data_knn$housing))
loan <- as.data.frame(dummy.code(data_knn$loan))
month <- as.data.frame(dummy.code(data_knn$month))
day_of_week <- as.data.frame(dummy.code(data_knn$day_of_week))
poutcome <- as.data.frame(dummy.code(data_knn$poutcome))
```

Rename “unknown” columns, so we don’t have duplicate columns later).

```
##  $ pdays         : num  0.195 0.195 0.195 0.195 0.195 ...
##  $ previous      : num  -0.349 -0.349 -0.349 -0.349 -0.349 ...
##  $ poutcome      : Factor w/ 3 levels "failure","nonexistent",..: 2 2 2 2
2 2 2 2 2 2 ...
```

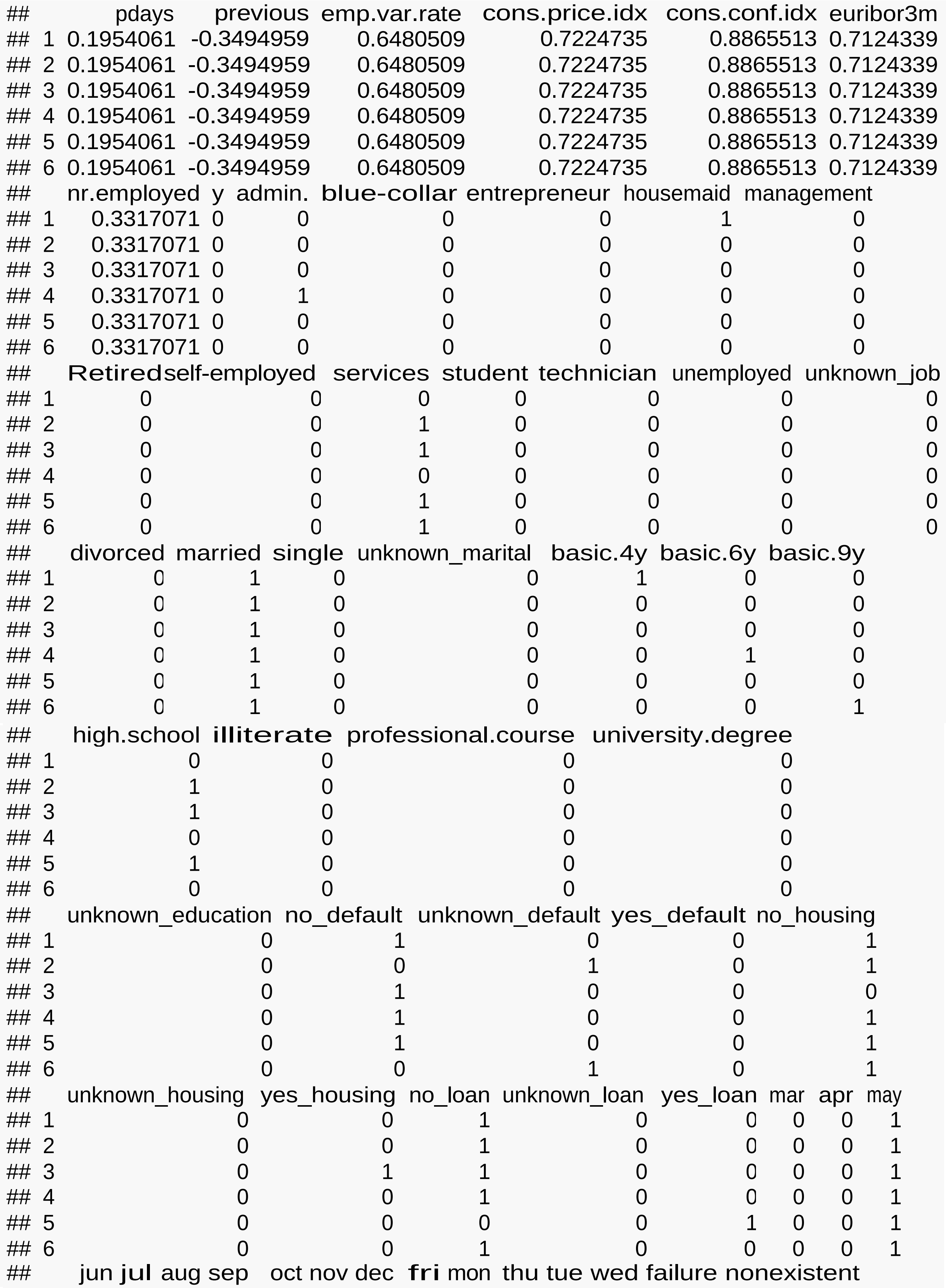
Combine new dummy variables with original data set.

```
## 'data.frame':    41163 obs. of  72 variables:
## $ age              : num  1.53368 1.62966 -0.28981 -0.00189 1.53368 ...
## $ 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          : num [1:41163, 1:2] 0 0 0 0 0 0 0 0 0 0 ...
##  ..- attr(*, "dimnames")=List of 2
##  .. ..$ : NULL
##  .. ..$ : chr  "cellular" "telephone"
## $ month            : Ord.factor w/ 10 levels "mar"<"apr"<"may"<..: 3 3
3 3 3 3 3 3 3 3 ...
## $ day_of_week      : Factor w/ 5 levels "fri","mon","thu",..: 2 2 2      2 2
2 2 2 2 2 ...
## $ duration         : num  0.0104 -0.4216 -0.1246 -0.4139 0.1878 ...
## $ campaign         : num  -0.566 -0.566 -0.566 -0.566 -0.566 ...
## $ pdays            : num  0.195 0.195 0.195 0.195 0.195 ...
## $ previous         : num  -0.349 -0.349 -0.349 -0.349 -0.349 ...
2 2 2 2 2 2 2 2  ...
## $ emp.var.rate     : num  0.648 0.648 0.648 0.648 0.648 ...
## $ cons.price.idx   : num  0.722 0.722 0.722 0.722 0.722 ...
## $ cons.conf.idx    : num  0.887 0.887 0.887 0.887 0.887 ...
## $ euribor3m        : num  0.712 0.712 0.712 0.712 0.712 ...
## $ nr.employed      : num  0.332 0.332 0.332 0.332 0.332 ...
## $ y                : num  0 0 0 0 0 0 0 0 0 0 ...
## $ admin.           : num  0 0 0 1 0 0 1 0 0 0 ...
## $ blue-collar      : num  0 0 0 0 0 0 0 1 0 0 ...
## $ entrepreneur     : num  0 0 0 0 0 0 0 0 0 0 ...
## $ housemaid        : num  1 0 0 0 0 0 0 0 0 0 ...
## $ management       : num  0 0 0 0 0 0 0 0 0 0 ...
## $ retired          : num  0 0 0 0 0 0 0 0 0 0 ...
## $ self-employed    : num  0 0 0 0 0 0 0 0 0 0 ...
## $ services         : num  0 1 1 0 1 1 0 0 0 1 ...
## $ student          : num  0 0 0 0 0 0 0 0 0 0 ...
## $ technician       : num  0 0 0 0 0 0 0 0 1 0 ...
## $ unemployed       : num  0 0 0 0 0 0 0 0 0 0 ...
## $ unknown_job      : num  0 0 0 0 0 0 0 0 0 0 ...
## $ divorced         : num  0 0 0 0 0 0 0 0 0 0 ...
## $ married          : num  1 1 1 1 1 1 1 1 0 0 ...
## $ single           : num  0 0 0 0 0 0 0 0 1 1 ...
## $ unknown_marital  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ basic.4y           : num  1 0 0 0 0 0 0 0 0 0 ...
##  $ basic.6y           : num  0 0 0 1 0 0 0 0 0 0 ...
##  $ basic.9y           : num  0 0 0 0 0 1 0 0 0 0 ...
##  $ high.school        : num  0 1 1 0 1 0 0 0 0 1 ...
##  $ illiterate         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ professional.course: num  0 0 0 0 0 0 1 0 1 0 ...
##  $ university.degree  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ unknown_education  : num  0 0 0 0 0 0 0 1 0 0 ...
##  $ no_default         : num  1 0 1 1 1 0 1 0 1 1 ...
##  $ unknown_default    : num  0 1 0 0 0 1 0 1 0 0 ...
##  $ yes_default        : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ no_housing         : num  1 1 0 1 1 1 1 1 0 0 ...
##  $ unknown_housing    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ yes_housing        : num  0 0 1 0 0 0 0 0 1 1 ...
##  $ no_loan            : num  1 1 1 1 0 1 1 1 1 1 ...
##  $ unknown_loan       : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ yes_loan           : num  0 0 0 0 1 0 0 0 0 0 ...
##  $ mar                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ apr                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ may                : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ jun                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ jul                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ aug                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ sep                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ oct                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ nov                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ dec                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ fri                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ mon                : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ thu                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ tue                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ wed                : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ failure            : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ nonexistent        : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ success            : num  0 0 0 0 0 0 0 0 0 0 ...
```

Remove original variables that had to be dummy coded.

```
data_knn <- data_knn %>% select(-one_of(c("job", "marital", "education", "default", "housing", "loan", "month", "day_of_week", "poutcome")))

head(data_knn)
```

```
##            age contact.cellular contact.telephone    duration  campaign
## 1  1.533684728                0                 1  0.01036255 -0.5658418
## 2  1.629657912                0                 1 -0.42162181 -0.5658418
## 3 -0.289805768                0                 1 -0.12463256 -0.5658418
## 4 -0.001886216                0                 1 -0.41390781 -0.5658418
## 5  1.533684728                0                 1  0.18778470 -0.5658418
## 6  0.477979704                0                 1 -0.23262865 -0.5658418
```



```
##          pdays    previous emp.var.rate cons.price.idx cons.conf.idx euribor3m
## 1 0.1954061  -0.3494959    0.6480509      0.7224735     0.8865513 0.7124339
## 2 0.1954061 -0.3494959     0.6480509      0.7224735     0.8865513 0.7124339
## 3 0.1954061 -0.3494959     0.6480509      0.7224735     0.8865513 0.7124339
## 4 0.1954061 -0.3494959     0.6480509      0.7224735     0.8865513 0.7124339
## 5 0.1954061 -0.3494959     0.6480509      0.7224735     0.8865513 0.7124339
## 6 0.1954061 -0.3494959     0.6480509      0.7224735     0.8865513 0.7124339
##   nr.employed y admin. blue-collar entrepreneur housemaid management
## 1   0.3317071 0      0           0            0         1          0
## 2   0.3317071 0      0           0            0         0          0
## 3   0.3317071 0      0           0            0         0          0
## 4   0.3317071 0      1           0            0         0          0
## 5   0.3317071 0      0           0            0         0          0
## 6   0.3317071 0      0           0            0         0          0
##   Retiredself-employed services student technician unemployed unknown_job
## 1       0             0        0       0          0          0           0
## 2       0             0        1       0          0          0           0
## 3       0             0        1       0          0          0           0
## 4       0             0        0       0          0          0           0
## 5       0             0        1       0          0          0           0
## 6       0             0        1       0          0          0           0
##   divorced married single unknown_marital basic.4y basic.6y basic.9y
## 1        0       1      0               0        1        0        0
## 2        0       1      0               0        0        0        0
## 3        0       1      0               0        0        0        0
## 4        0       1      0               0        0        1        0
## 5        0       1      0               0        0        0        0
## 6        0       1      0               0        0        0        1
##   high.school illiterate professional.course university.degree
## 1           0          0                   0                 0
## 2           1          0                   0                 0
## 3           1          0                   0                 0
## 4           0          0                   0                 0
## 5           1          0                   0                 0
## 6           0          0                   0                 0
##   unknown_education no_default unknown_default yes_default no_housing
## 1                 0          1               0           0          1
## 2                 0          0               1           0          1
## 3                 0          1               0           0          0
## 4                 0          1               0           0          1
## 5                 0          1               0           0          1
## 6                 0          0               1           0          1
##   unknown_housing yes_housing no_loan unknown_loan yes_loan mar apr may
## 1               0           0       1            0        0   0   0   1
## 2               0           0       1            0        0   0   0   1
## 3               0           1       1            0        0   0   0   1
## 4               0           0       1            0        0   0   0   1
## 5               0           0       0            0        1   0   0   1
## 6               0           0       1            0        0   0   0   1
##   jun jul aug sep oct nov dec fri mon thu tue wed failure nonexistent
## 1    0    0    0    0    0    0    0    0    1    0    0    0          0              1
## 2    0    0    0    0    0    0    0    0    1    0    0    0          0              1
## 3    0    0    0    0    0    0    0    0    1    0    0    0          0              1
## 4    0    0    0    0    0    0    0    0    1    0    0    0          0              1
## 5    0    0    0    0    0    0    0    0    1    0    0    0          0              1
## 6    0    0    0    0    0    0    0    0    1    0    0    0          0              1
##     success
## 1         0
## 2         0
## 3         0
## 4         0
## 5         0
## 6         0
```

We are now ready for k-NN classification. We split the data into training and test sets. We partition 80% of the data into the training set and the remaining 20% into the test set.

Splitting the dataset into Test and Train:

```
set.seed(1234) # set the seed to make the partition  reproducible

# 80% of the sample size
sample_size <- floor(0.8 * nrow(data_knn))


train_index <- sample(seq_len(nrow(data_knn)), size = sample_size)

# put outcome in its own object
knn_outcome <- data_knn %>% select(y)

# remove original variable from the data set
data_knn <- data_knn %>% select(-y)

# creating test and training sets that contain all of the predictors
knn_data_train <- data_knn[train_index,]
knn_data_test <- data_knn[-train_index,]

# Split outcome  variable into training and  test sets using the same  partition
as  above.
knn_outcome_train <- knn_outcome[train_index, ]
knn_outcome_test <- knn_outcome[-train_index, ]
```

Using ‘class’ package, we run k-NN categorization on our data. We have to make a decision on the number of neighbors (k).This is an iterative exercise as we need to keep changing the value of k to dtermine the optimum performance. In our case, we started with k=10 till k=20, and finally got an optimum performance at k=17.

```
model_knn <- knn(train = knn_data_train, test = knn_data_test, cl = knn_outco
me_train, k=17)
```

Model evaluation:

```
# put "knn_outcome_test" in a data frame
knn_outcome_test <- data.frame(knn_outcome_test)

# merge "model_knn" and "knn_outcome_test"
knn_comparison_df <- data.frame(model_knn, knn_outcome_test)

# specify column names for "knn_comparison_df"
names(knn_comparison_df) <- c("KNN_Predicted_y", "KNN_Observed_y")

knn_comparison_df$KNN_Predicted_y <- as.factor(knn_comparison_df$KNN_Predicte
d_y)
knn_comparison_df$KNN_Observed_y <- as.factor(knn_comparison_df$KNN_Observed_
y)

# inspect "knn_comparison_df"
head(knn_comparison_df)

##     KNN_Predicted_y  KNN_Observed_y
## 1                 0               0
## 2                 0               0
## 3                 0               0
## 4                 0               0
## 5                 0               0
## 6                 0               0
```

Next, we evaluate our predict values of deposit to our actual values. The confusion matrix gives an indication of how well our model predicted the actual values. The confusion matrix output also shows overall model statistics and statistics by class

```
confusionMatrix(knn_comparison_df$KNN_Observed_y,knn_comparison_df$KNN_Predic
ted_y)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 7071  179
##          1  586  397
##
##                Accuracy : 0.9071
##                  95% CI : (0.9006, 0.9133)
##     No Information Rate : 0.93
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4618
```

```
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9235
##             Specificity : 0.6892
##          Pos Pred Value : 0.9753
##          Neg Pred Value : 0.4039
##              Prevalence : 0.9300
##          Detection Rate : 0.8589
##    Detection Prevalence : 0.8806
##       Balanced Accuracy : 0.8064
##
##        'Positive' Class : 0
##
```

The K-NN test data consisted of 8238 interpretation. Out of which 7128 cases have been accurately predicted (TN->True Negatives) as negative class (0) which constitutes 87%. Also, 367 out of 8238 observations were accurately predict (TP-> True Positives) as positive class (1) which constitutes 4%. Thus a total of 367 out of 8238 predictions where TP i.e, True Positive in nature.

There were 544 cases of False Positives (FP) meaning 544 cases out of 8238 were actually negative but got predict as positive.

There were 199 cases of False Negatives (FN) meaning 199 cases were actually positive in nature but got predict as negative.

Accuracy of the model is the correctly classified positive and negative cases divided by all the cases. The total accuracy of the model is 91.13%, which means the model prediction is very accurate.

3. Conclusion

Model Comparison

K Nearest Neighbor are generating high accuracy when trained with the bank marketing dataset.

The parameter K-NN model is:

Parameter	K-NN Model
Accuracy	91.13%
Sensitivity	93.03%
Specificity	65.68%
Pos Pred Value	97.31%
Neg Pred Value	41.38%

Analysis Summary

The key insight derived from the in general analysis are:

- People who aren't in default are a higher amount of people who have subscribe for bank deposits.

- Higher quantity of people who have subscribe for bank deposit are home owners versus ones that don't own their own houses.

-With respect to Marital Status, there is not an experiential large difference in the proportion of people subscribed to term deposits and people without term deposits.

- The proportion of people who have subscribed and not subscribed to a term deposit is the same for categories of the Loan.

- Customers who sign up for bank deposits, proportionally, have achieved a higher level of education, than those who didn't sign up.

- The months of April, September, October, and December is the time when a higher proportion of people subscribed for term deposits.

- There are higher proportions for customers signing up for the term deposits who have the jobs of admin, retired, and students.

- Customers who have cell phones, and therefore a more direct way of communicating, signed up for term deposits more than those who only had a landline telephone.

- The age range for successful conversion has a slightly lower median, but higher quartile ranges.

- Campaigns that were performed midweek, on Tuesdays, Wednesdays, and Thursdays had a slightly higher proportion of people who subscribed for bank deposit.

- Potential customers who successfully connected and responded in previous campaigns had a higher proportion of signing up for the term deposit.

- The longer the phone conversation the greater the conversion rate is for the potential customer to sign up for the term deposit. There are higher median and quartile ranges.

- Subscribing to term deposit has a high positive correlation with duration and if the customer was involved and connected in a previous campaign, while there's negative correlation with Nr.employed (number of employees), pdays (number of days from last contact), Euribor3m (Euribor 3 month rate) and emp.var.rate (employee variation rate).

Target Market Strategy

The business problem defined in the introduction is to devise a target marketing strategy for the bank based on the behavioral data collected. We discovered the kinds of observations and behaviors of potential customers that result in them more likely to subscribe to a term deposit.

Using the above insights, the bank should devise a target marketing strategy that is customized towards potential customers with those who already have an existing account with the bank and have higher education. Those customers who generally are either employed in admin related jobs, or are students, or retired are those the bank can further pull.

Those customers who are easily accessible with a mobile number will be the ones to answer the call, the key is to have an engaging and personable conversation with the customer and establish a relationship where they feel comfortable signing up for a term deposit with the bank. Those customers who were part of the previous campaign should be contacted by the bank again because we saw following up and having a continued dialogue and relationship results in a higher number of those who sign up. Also, in order to improve the probability of success, the campaigns should be launched in the last third of the calendar year when people are thinking of saving for the future and preparing for year-end taxes.

Future Work

Data analytics is usually used to examine and work with big data such as the one we provided in the project here. It eases the cross-examination of the data and the methods of finding relationships within the data, so it becomes easier. There is a lo t of things that we can do in future upon the existing model such as determining the right day of the week and time for each of the target audience or build custom models for individual clusters to further improve the prediction rate and reduce the error rate.

The work that has been done on this modeling and analysis is a great start for the bank to acquire more customers in an efficient way. There can always be improvements and tweaking as more data comes in, as well as exploring niches and clusters within the data. What a great start to enhancing the target market strategy!