"Predicting Customer Penetration For a Banking Product"

TERM PROJECT REPORT

(EMBA-408)

Under the Guidance of

Dr. Deepali Malhotra

by

Aditya Vasishta

(23/EMBA/02)

Delhi School of Management, Delhi Technological University Delhi

DECLARATION

I, Aditya Vasishta, a student of MBA(E) 2023-25 at Delhi School of Management, Delhi Technological University, Bawana Road, Delhi - 42, hereby declare that the report "Predicting Customer Penetration For a Banking Product" submitted in partial fulfillment of the degree of Masters of Business Administration (Executive) is my original work.

To the best of my knowledge, the facts and data included in the report are accurate.

This report is not being submitted to any other university for the awarding of a degree, diploma, or fellowship.

Place : Name and Signature

Date:

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to everyone who contributed to the successful completion of this project. It is my great pleasure to extend my sincere appreciation to **Dr. Deepali Malhotra**, whose thorough instruction and continuous support were immensely valuable to both the theoretical and practical aspects of this work. Her mentorship played a crucial role in guiding my approach and deepening my understanding throughout the project.

This opportunity represents a significant step forward in my professional development. I will strive to apply my acquired skills and knowledge to the best of my ability, and I will continue to work on improving them in order to achieve my career goals. I want to continue cooperating with all of you in the future.

Sincerely,

Aditya Vasishta

DTU (DSM)

Date:

EXECUTIVE SUMMARY

This project aims to develop a predictive model to identify customers most likely to subscribe to a term deposit product, using historical campaign data from a Portuguese bank. Given the class imbalance, SMOTE was applied for data balancing. Multiple models were tested including Logistic Regression, Decision Tree, and Random Forest, on both balanced and unbalanced datasets.

Key Findings:

- Customers aged 35–60 and those with call durations over 3 minutes are more likely to subscribe.
- Success in past campaigns significantly predicts future conversions.
- SMOTE-enhanced models outperformed their non-SMOTE counterparts in detecting positive responses.

Best Model Selected: Logistic Regression (on SMOTE data)
Accuracy: 86.2% | **Sensitivity:** 95.1% | **Kappa:** 0.726

Actionable Insight:
The model can help the bank reduce irrelevant outreach by focusing only on high-likelihood customers, thus improving customer experience and campaign efficiency.

TABLE OF CONTENTS

1. Introduction
2. Background and Problem Statement
3. Study Objectives
4. Product Scope
5. Research Methodology
    a. Data-Set & Attribute Information
    b. Import Libraries
    c. Import and Introduction to DataSet
    d. Categorical Treatment
    e. Feature Engineering
    f. SMOTE Algorithm For Unbalanced Classification Problems
    a. d. Data Splitting | Building Training and Testing Data sets
    b. e. Applying Prediction Models
    g. Conclusion | Evaluating Different Models
6. Findings & Outcomes
7. Conclusion & Recommendations
8. References

INTRODUCTION

In today’s highly competitive financial landscape, the success of a bank increasingly hinges on its ability to offer the right products to the right customers at the right time. With the proliferation of customer data and the emergence of machine learning technologies, there is a significant opportunity for banks to enhance their marketing strategies through intelligent and data-driven decision-making. This project report presents a comprehensive approach to solving a key challenge faced by a banking institution: identifying the most likely customers to subscribe to a newly launched term deposit product.

The bank in question is currently facing a serious gap in its marketing process. With no framework to differentiate between interested and uninterested customers, the bank resorts to contacting all customers indiscriminately. This untargeted approach has led to an increase in customer complaints regarding irrelevant and intrusive marketing calls, ultimately causing dissatisfaction and a negative perception of the bank's outreach strategies. Moreover, such a method is not only inefficient in terms of resources but also fails to maximize the conversion potential of the bank’s marketing efforts.

To address this problem, the bank aims to leverage historical marketing campaign data that includes information on customer demographics, economic context, communication history, and past responses. The goal is to design a predictive system that can effectively segment the customer base and prioritize outreach to individuals most likely to subscribe to the term deposit product. By doing so, the bank can streamline its marketing activities, reduce unnecessary customer interactions, and achieve a higher return on investment.

This project utilizes supervised machine learning algorithms to develop a classification model that predicts whether a customer is likely to buy the term deposit product. The dataset used for this project comprises over 41,000 records, with attributes ranging from personal information such as age, job type, and education level to campaign-specific details such as contact duration, call month, and response outcome. Preliminary data exploration revealed class imbalance in the dataset, with significantly more 'no' responses than 'yes' responses, which necessitated the use of Synthetic Minority Oversampling Technique (SMOTE) to ensure balanced model training.

The methodology adopted in this project follows a structured pipeline. First, extensive exploratory data analysis (EDA) was conducted to understand feature distributions, identify missing values, and uncover relationships between variables and customer responses. Categorical variables were treated, and features were engineered based on domain understanding—for instance, grouping age and call duration into meaningful categories based on their predictive significance. Highly correlated economic indicators were also analyzed to eliminate redundancy and improve model efficiency.

Following data preprocessing, multiple classification models were applied, including Logistic Regression, Decision Trees, and Random Forests. The models were trained and validated on both SMOTE-balanced and original datasets to compare their effectiveness in handling class imbalance. Each model's performance was assessed using standard metrics such as accuracy, sensitivity, specificity, ROC curves, and confusion matrices. In addition, feature importance analysis was carried out to identify key drivers influencing customer decisions.

PROBLEM STATEMENT

As part of its strategic initiative to deepen relationships with existing customers, a bank is launching a new term deposit product. The bank plans to reach out to its customer base to promote and upsell this offering. However, in executing past marketing campaigns, the bank has encountered a critical challenge—customers have raised complaints about receiving irrelevant and excessive marketing calls. These calls, often indiscriminately made to all customers without regard to individual interest or suitability, have led to growing dissatisfaction and reputational risk.

The underlying issue is the absence of a data-driven framework that can distinguish between likely and unlikely buyers of the product. Without such a mechanism in place, the bank's current approach relies heavily on blanket outreach, which is both inefficient and counterproductive. Moreover, the bank has ruled out manual shortlisting of potential customers due to the risk of human bias and the inefficiencies associated with such subjective interventions.

However, a valuable asset already exists: historical data from previous campaigns, including customer demographics, campaign details, and whether the offer was accepted or declined. This dataset presents a promising opportunity to develop a predictive model using supervised machine learning algorithms. The objective is to analyze past patterns to identify the characteristics of customers who are more inclined to subscribe to the term deposit.

By adopting this predictive approach, the bank aims to transition to a more targeted and automated marketing strategy. Such a model would not only reduce unnecessary communication with uninterested clients but also improve conversion rates and streamline marketing efforts.

OBJECTIVES

1. To analyze historical campaign data and understand key factors influencing customer decisions.

2. To apply supervised machine learning techniques for binary classification (subscription: *yes* or *no*).

3. To address class imbalance in the dataset using methods like SMOTE (Synthetic Minority Over-sampling Technique).

4. To evaluate and compare multiple classification models (e.g., Logistic Regression, Decision Trees, Random Forest) based on accuracy, sensitivity, and other relevant performance metrics.

5. To recommend the most effective model for deployment in the bank's customer outreach system.

6. To design a scalable and automated framework for targeted marketing with minimal manual intervention.

PRODUCT SCOPE

1. **Understanding and Data Pre-Processing**
    a. The data set consists of customer characteristics, campaign characteristics, previous campaign information as well as whether customer ended up subscribing to the product as a result of that campaign or not.
    b. The data will be cleansed for any irregularities and some of the categorical attributes of data sets will be masked to continuous values in order to prepare the data feed for building model.
2. **Exploratory Data Analysis**
    a. Here we will perform initial investigations on data to discover any patterns, to spot anomalies and to check assumptions with help of summary statistics and graphical representations.
3. **Feature Engineering**
    a. Based on understanding build out of data, applying certain domain knowledge and identifying correlations among different attributes few important attributes from data sets will be identified that better represents the underlying problem to the predictive models in form of inputs that the algorithm can understand.
4. **Data Splitting and Applying Classification Models**
    a. As per standard best practices, 70% of random records from dataset will be used as Training Data on which the model will be built and 30% of data will be used to test the model performance. Classification techniques based out of Logistic Regression and Decision Tree will be used to build the predictive model.
5. **Model Evaluation**
    a. Certain metrics such as Confusion Metrics, Precision, Recall, Accuracy etc.., will be used to evaluate the model performance on different algorithms and the predictions from the model with better evaluation metrics can be considered for targeted product promotion.

RESEARCH METHODOLOGY

Data-Set Information

The dataset used in this project originates from a Portuguese banking institution's direct marketing campaigns, focused on promoting term deposit subscriptions. The data captures detailed information about customer profiles, past marketing interactions, and corresponding outcomes, making it suitable for supervised classification modeling.

The dataset contains **41,188 records** and **21 input features**, along with **1 output variable** (y), which indicates whether a customer subscribed to the term deposit (yes or no). The features span across three major categories:

- **Client Information**: Attributes such as age, job type, marital status, education level, and existing financial commitments (e.g., housing or personal loans).
- **Campaign Details**: Information from previous marketing campaigns, including contact method, timing (month, day), call duration, number of contacts, and previous outcomes.
- **Economic Indicators**: Macro-level attributes like employment variation rate, consumer confidence index, and Euribor 3-month rate, which may influence customer decision-making.

The dataset does not contain null values in the traditional sense, but several features include the category "unknown," which has been treated as a placeholder for missing or non-disclosed information. These aspects were addressed during data preprocessing and feature engineering stages of the project.

Attribute Information

1) Age
2) Job : type of job

3) Marital : marital status
4) Education: Type of education
5) Default: has credit in default?
6) Housing: has housing loan?
7) Loan: has personal loan?
8) Contact: contact communication type
9) Month: last contact month of year
10) Day_of_week: last contact day of the week
11) Duration: last contact duration, in seconds
12) Campaign: number of contacts performed during this campaign and for this client
13) Pdays: number of days that passed by after the client was last contacted from a previous campaign
14) Previous: number of contacts performed before this campaign and for this client
15) Poutcome: outcome of the previous marketing campaign
16) Social and economic context attributes
17) Emp.var.rate: employment variation rate - quarterly indicator
18) Cons.price.idx: consumer price index - monthly indicator
19) Cons.conf.idx: consumer confidence index - monthly indicator
20) Euribor3m: euribor 3 month rate - interest rate at which a panel of banks lend money to one another with a maturity of 3 months
21) Nr.employed: number of employees - quarterly indicator
22) Output variable (desired target):y - has the client subscribed a term deposit?

Import Libraries

In [1]:

```
library(dplyr)
library(tidyr)
library(ggplot2)
library(ggmosaic)
library(gmodels)
library(corrplot)
library(DMwR2)
library(ROCR)
library(caret)
library(rpart)
library(smotefamily)
library(rpart.plot)
library(randomForest)
```

```
Attaching package: ‘dplyr’

The following objects are masked from ‘package:stats’:

    filter, lag

The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union

corrplot 0.92 loaded

Registered S3 method overwritten by 'quantmod':

  method            from

  as.zoo.data.frame zoo

Loading required package: lattice

randomForest 4.7-1.1

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

Attaching package: ‘randomForest’

The following object is masked from ‘package:ggplot2’:

    margin

The following object is masked from ‘package:dplyr’:

    combine
```

1 Import and Introduction to DataSet

1.1 Input the Data File

In [2]:

```
InputData = read.csv(file = " bank-additional-full.csv" ,sep = ";"
,stringsAsFactors = F)

dim(InputData)
```

41188 · 21

The dataset has **41,188 rows** and **21 Columns**

1.2 Know the DataSet

In [3]:

```
names(InputData)
```

'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' · 'y'

The First 20 columns seems to be **"potential explanatory variables"** or independent variables and the column named **"y" is the dependent variable**

1.3 Looking at the sample Data

In [4]:

```
head(InputData)
```

A data.frame: 6 × 21

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	⋯	campaign	pdays	previous	poutcome	emp.var.rate	cons.p
	<int>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	⋯	<int>	<int>	<int>	<chr>	<dbl>	
1	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	
2	57	services	married	high.school	unknown	no	no	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	
3	37	services	married	high.school	no	yes	no	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	
4	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	
5	56	services	married	high.school	no	no	yes	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	
6	45	services	married	basic.9y	unknown	no	no	telephone	may	mon	⋯	1	999	0	nonexistent	1.1	

1.4 Identifying the datatypes of all the columns

In [5]:

```
sapply(InputData,typeof)
```

age: 'integer' **job:** 'character' **marital:** 'character' **education:** 'character' **default:** 'character' **housing:** 'character' **loan:** 'character' **contact:** 'character' **month:** 'character' **day_of_week:** 'character' **duration:** 'integer' **campaign:** 'integer' **pdays:** 'integer' **previous:** 'integer' **poutcome:** 'character' **emp.var.rate:** 'double' **cons.price.idx:** 'double' **cons.conf.idx:** 'double' **euribor3m:** 'double' **nr.employed:** 'double' **y:** 'character'

1.5 Check if any of the columns have null values

In [6]:

```
sapply(InputData,is.null)
```

age: FALSE **job:** FALSE **marital:** FALSE **education:** FALSE **default:** FALSE **housing:** FALSE **loan:** FALSE **contact:** FALSE **month:** FALSE **day_of_week:** FALSE **duration:** FALSE **campaign:** FALSE **pdays:** FALSE **previous:** FALSE **poutcome:** FALSE **emp.var.rate:** FALSE **cons.price.idx:** FALSE **cons.conf.idx:** FALSE **euribor3m:** FALSE **nr.employed:** FALSE **y:** FALSE

None of the columns in our dataset have any **missing or null values**, however according to the documentation we know there is variable defined as **"unknown"** which is equivalent to null

1.6 Identifying the unknowns in the DataSet

In [7]:

```
InputData %>%
summarise_all(list(~sum(. == "unknown"))) %>%
gather(key = "Column Name", value = "No._of_Unknowns") %>%
arrange(-No._of_Unknowns)

### Total Unknowns in all Columns ###
TotalUnknowns <- sum(InputData == "unknown")
TotalUnknowns <- cat("Total Number of Unknowns in all Columns in DataSet are",TotalUnknowns)
```

A data.frame: 21 × 2

Column Name	No._of_Unknowns
<chr>	<int>
default	8597
education	1731
housing	990
loan	990
job	330
marital	80
age	0
contact	0
month	0
day_of_week	0
duration	0
campaign	0
pdays	0
previous	0
poutcome	0
emp.var.rate	0
cons.price.idx	0
cons.conf.idx	0
euribor3m	0
nr.employed	0
y	0

```
Total Number of Unknowns in all Columns in DataSet are 12718
```

6 of the features in the DataSet seems to have atleast one of there values as **"unknown"**

2 Exploratory Data Analysis

2.1 Seggregating Data as per functional unserstanding of dataset

In [8]:

```
ClientPII <- select(InputData,1,2,3,4,5,6,7,21)
head(ClientPII)
```

A data.frame: 6 × 8

	age	job	marital	education	default	housing	loan	y
	<int>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>
1	56	housemaid	married	basic.4y	no	no	no	no
2	57	services	married	high.school	unknown	no	no	no
3	37	services	married	high.school	no	yes	no	no
4	40	admin.	married	basic.6y	no	no	no	no
5	56	services	married	high.school	no	no	yes	no
6	45	services	married	basic.9y	unknown	no	no	no

The above 7 columns serve as **Non Sensitive Personal Identifiable Information (PII)** of the client thus seggreagted together in ClientPII DataFrame

In [9]:

```
PreviousCampaign <- select(InputData,8,9,10,11,12,13,14,15,21)
head(PreviousCampaign)
```

A data.frame: 6 × 9

	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	y
	<chr>	<chr>	<chr>	<int>	<int>	<int>	<int>	<chr>	<chr>
1	telephone	may	mon	261	1	999	0	nonexistent	no
2	telephone	may	mon	149	1	999	0	nonexistent	no
3	telephone	may	mon	226	1	999	0	nonexistent	no
4	telephone	may	mon	151	1	999	0	nonexistent	no
5	telephone	may	mon	307	1	999	0	nonexistent	no
6	telephone	may	mon	198	1	999	0	nonexistent	no

The above columns can help in understanding attributes related to last contact with clients as part of previous campaign

In [10]:

```
EconomicContext <- select(InputData,16:20)
head(EconomicContext)
```

A data.frame: 6 × 5

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	1.1	93.994	-36.4	4.857	5191
2	1.1	93.994	-36.4	4.857	5191
3	1.1	93.994	-36.4	4.857	5191
4	1.1	93.994	-36.4	4.857	5191
5	1.1	93.994	-36.4	4.857	5191
6	1.1	93.994	-36.4	4.857	5191

These columns like employee variation rate (quaterly indicator) consumer price index (monthly indicator) and others constitues in building Economic Context

2.2 Performing EDA on Client's PII

2.2.1 Understanding Categorical Values

2.2.1.1 Marital Status

In [11]:

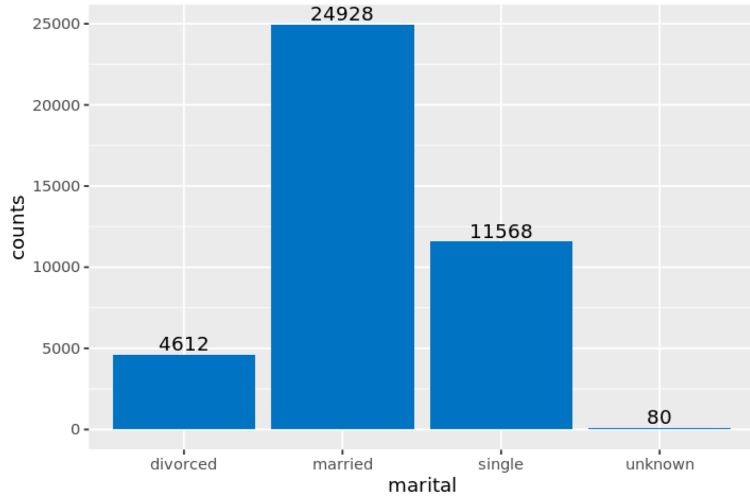
```
table(ClientPII$marital)
```

```
divorced   married    single  unknown 
    4612     24928     11568       80 
```

The above table shows unqiue values in marital attribute of the dataset

In [12]:

```
MaritalDF <- ClientPII %>% group_by(marital) %>% summarise(counts = n())
options(repr.plot.width = 6, repr.plot.height = 4)
ggplot(MaritalDF, aes(x = marital, y = counts)) + geom_bar(fill = "#0073C2FF", stat = 

"identity") + geom_text(aes(label = counts), vjust = -0.3)
```

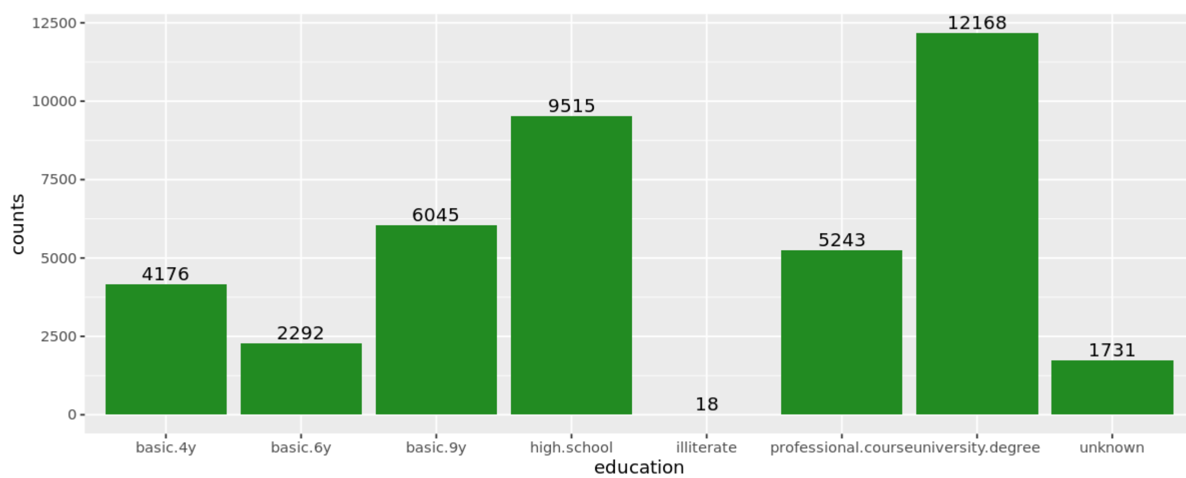


The above figure is graphical representation of stats for marital attributes which depicts most of the bank clients are **married**.

2.2.1.2 Education

In [13]:

```
EducationDF <- ClientPII %>% group_by(education) %>%
summarise(counts = n())
options(repr.plot.width = 10, repr.plot.height = 4)
ggplot(EducationDF, aes(x = education, y = counts)) + geom_bar(fill = "#228B22", stat
= "identity") +
geom_text(aes(label = counts), vjust = -0.3)
```



Above is graphical representation of education status of bank employees

2.2.1.3 Jobs

In [14]:

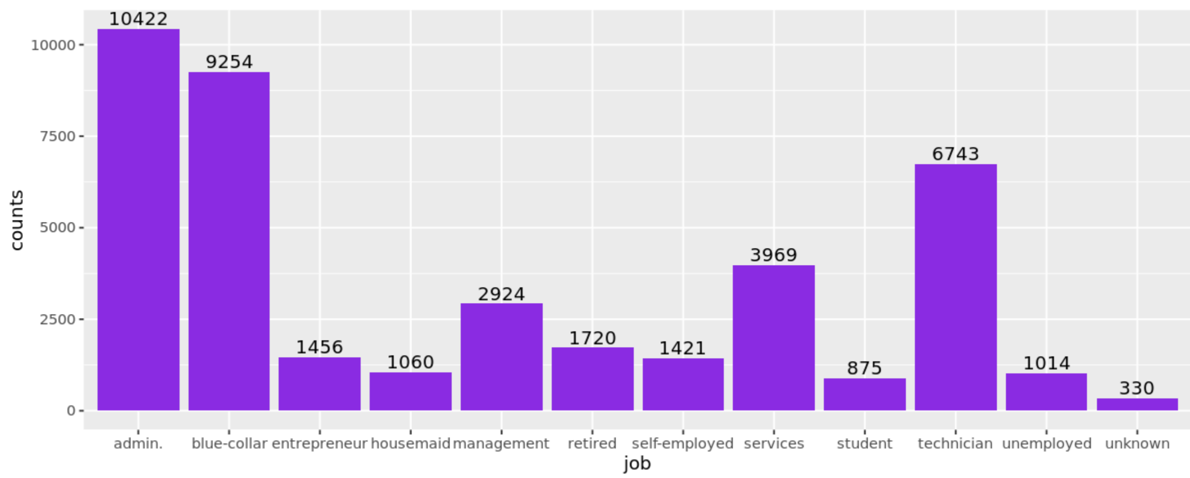
```
table(ClientPII$job)
```

```
      admin.    blue-collar   entrepreneur    housemaid   management 
       10422           9254           1456         1060         2924 
     retired  self-employed       services      student   technician 
        1720           1421           3969          875         6743 
  unemployed        unknown 
        1014            330 
```

Graphical Representation

In [15]:

```
JobDF <- ClientPII %>% group_by(job) %>% summarise(counts = n())
options(repr.plot.width = 10, repr.plot.height = 4)
ggplot(JobDF, aes(x = job, y = counts)) + geom_bar(fill = "#8A2BE2", stat = 
"identity") + geom_text(aes(label = counts), vjust = -0.3)
```



We observe the most of the bank clients are working in **adminstrative jobs** followed by **blue-collar jobs** whereas as job status of 330 clients are unknown

Crossing and Plotting types of Jobs with #clients buying term deposit

In [16]:

```
CrossTable(ClientPII$job,ClientPII$y,prop.r=TRUE, prop.c=FALSE,prop.t=FALSE, 
prop.chisq=FALSE, chisq = FALSE)
## Here prop.r specifies Row Proportion, prop.c Column Proportion, prop.t Table Proportion 
etc..
```

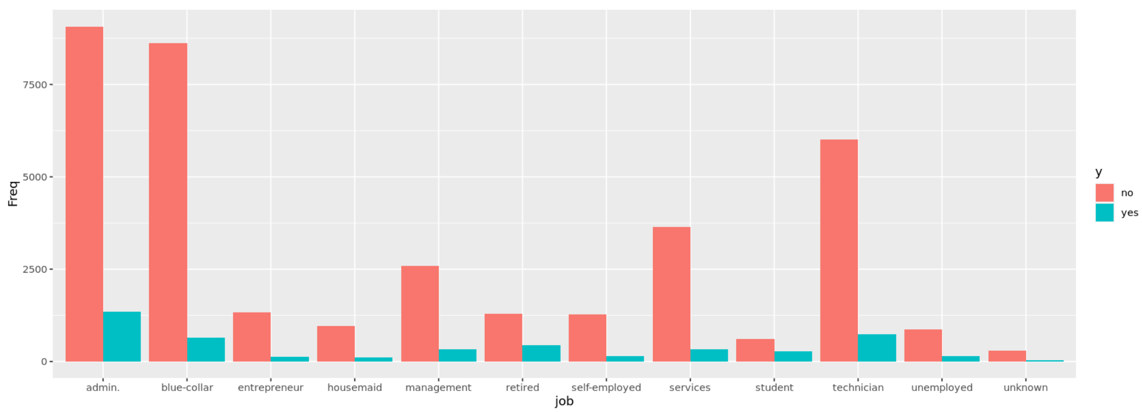
```
   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|-------------------------|


Total Observations in Table:  41188 


              | ClientPII$y 
```

```
ClientPII$job |        no |       yes | Row Total |
--------------|-----------|-----------|-----------|
       admin. |      9070 |      1352 |     10422 |
              |     0.870 |     0.130 |     0.253 |
--------------|-----------|-----------|-----------|
  blue-collar |      8616 |       638 |      9254 |
              |     0.931 |     0.069 |     0.225 |
--------------|-----------|-----------|-----------|
 entrepreneur |      1332 |       124 |      1456 |
              |     0.915 |     0.085 |     0.035 |
--------------|-----------|-----------|-----------|
    housemaid |       954 |       106 |      1060 |
              |     0.900 |     0.100 |     0.026 |
--------------|-----------|-----------|-----------|
   management |      2596 |       328 |      2924 |
              |     0.888 |     0.112 |     0.071 |
--------------|-----------|-----------|-----------|
      retired |      1286 |       434 |      1720 |
              |     0.748 |     0.252 |     0.042 |
--------------|-----------|-----------|-----------|
self-employed |      1272 |       149 |      1421 |
              |     0.895 |     0.105 |     0.035 |
--------------|-----------|-----------|-----------|
     services |      3646 |       323 |      3969 |
              |     0.919 |     0.081 |     0.096 |
--------------|-----------|-----------|-----------|
      student |       600 |       275 |       875 |
              |     0.686 |     0.314 |     0.021 |
--------------|-----------|-----------|-----------|
   technician |      6013 |       730 |      6743 |
              |     0.892 |     0.108 |     0.164 |
--------------|-----------|-----------|-----------|
   unemployed |       870 |       144 |      1014 |
              |     0.858 |     0.142 |     0.025 |
--------------|-----------|-----------|-----------|
      unknown |       293 |        37 |       330 |
              |     0.888 |     0.112 |     0.008 |
--------------|-----------|-----------|-----------|
 Column Total |     36548 |      4640 |     41188 |
--------------|-----------|-----------|-----------|
```

Graphical Representation

In [17]:

```
GraphData <- rename(count(ClientPII, job, y), Freq = n)
options(repr.plot.width = 14, repr.plot.height = 5)
JobGraph <- ggplot(GraphData, aes(job, Freq)) + geom_bar(aes(fill = y), stat =
"identity", position = "dodge")
JobGraph
```



The above table shows **maximum** number of term deposits are being bought by Clients involved in **adminstrative jobs** followed with **blue collar jobs** which is completely in sync with the above observation where it was discovered that most of the cleints of bank are invloved in adminstrative jobs followed by blue collar jobs

2.2.1.4 Others

In [18]:

```
DefaultDF <- ClientPII %>% group_by(default) %>% summarise(counts = n())
HousingDF <- ClientPII %>% group_by(housing) %>% summarise(counts = n())
LoanDF <- ClientPII %>% group_by(loan) %>% summarise(counts = n())
DefaultDF
HousingDF
LoanDF
```

A tibble: 3 × 2

default	counts
<chr>	<int>
no	32588
unknown	8597
yes	3

A tibble: 3 × 2

housing	counts
<chr>	<int>
no	18622
unknown	990
yes	21576

A tibble: 3 × 2

loan	counts
<chr>	<int>
no	33950
unknown	990
yes	6248

Here we have counts for **#clients** which have **default credits or have housing loan or any other type of loan**

2.2.2 Age

Looking at **Maximum & Minimum** Age of bank's client

In [19]:

```
summary(ClientPII$age)
```

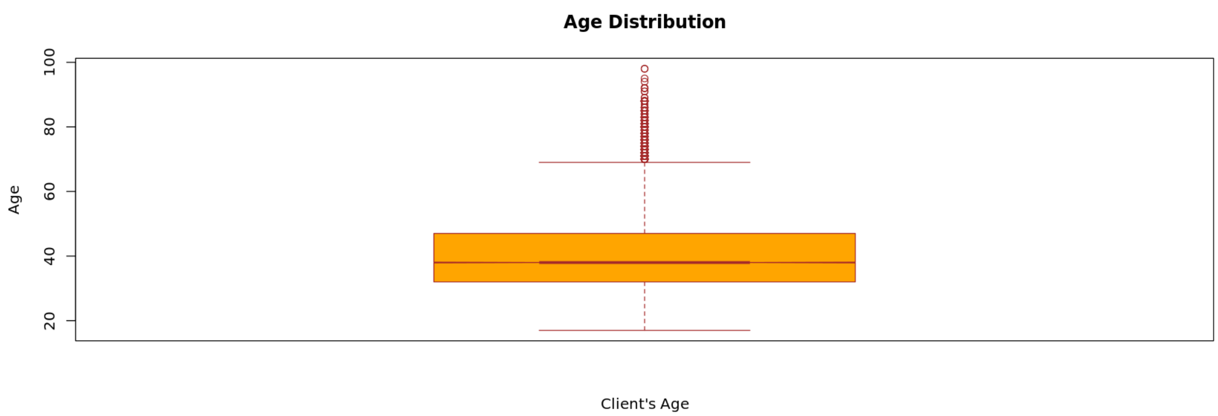
```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  17.00   32.00   38.00   40.02   47.00   98.00 
```

The above summary of **age** attribute describes **Maximum Age** as **98** and **Minimum Age** as **17** whereas the

Mean Age is **40 Plotting Age distribution of Client's Age to determine the interval where most of the bank client resides**

In [20]:

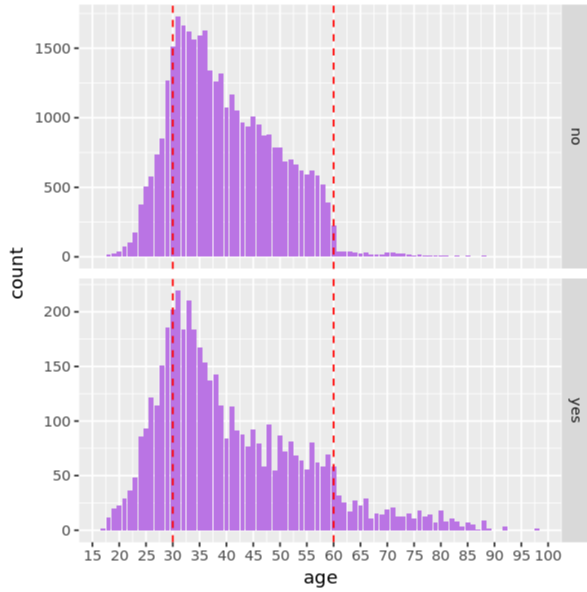
```
boxplot(ClientPII$age,
main = "Age Distribution",xlab = "Client's Age",ylab = "Age",col =
"orange",border = "brown", #horizontal = TRUE,
notch = TRUE)
options(repr.plot.width = 5, repr.plot.height = 5)
```



Determining the age groups of clients who bought and did not bough the term deposit

In [21]:

```
ClientPII %>%
ggplot() +
aes(x = age) +
geom_bar(fill = '#BA74E4') +
geom_vline(xintercept = c(30, 60),
col = "red",
linetype = "dashed") +
facet_grid(y ~ .,
scales = "free_y") +
scale_x_continuous(breaks = seq(0, 100, 5))
```



2.3 Performing EDA on Previous Campaign attributes

2.3.1 Contact | How was the client contacted in previous campaign

In [22]:

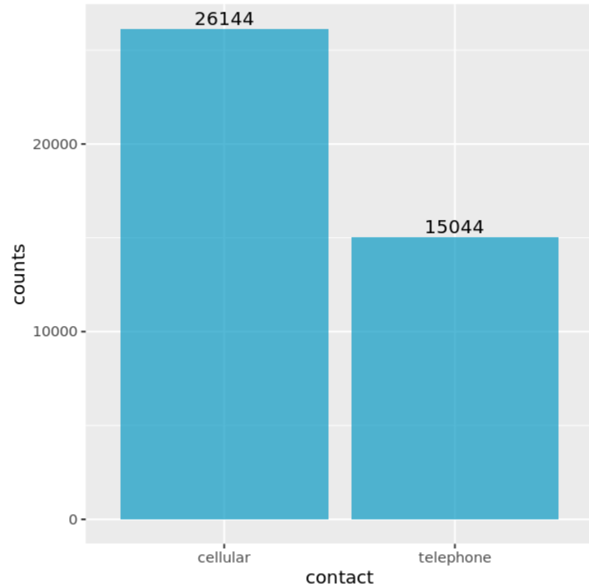
```
DurationDF <- PreviousCampaign %>% group_by(contact) %>%
summarise(counts = n())

DurationDF
```

A tibble: 2 × 2

contact	counts
<chr>	<int>
cellular	26144
telephone	15044

In [23]:

```
ggplot(DurationDF, aes(x = contact, y = counts)) +
geom_bar(fill = "#0096C2AA", stat = "identity") +
geom_text(aes(label = counts), vjust = -0.3)
```



The above summary of **contact** attribute describes most of the bank clients were previously contacted on their celluar phones

2.3.2 Month | In which month the campaign

In [24]:

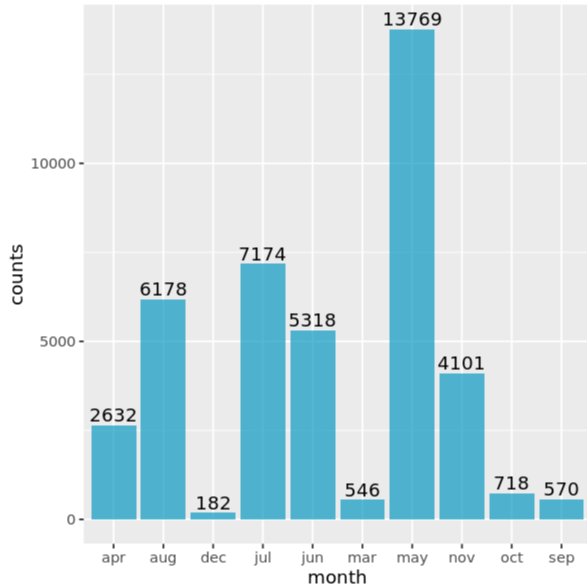
```
MonthDF <- PreviousCampaign %>% group_by(month) %>%
summarise(counts = n())

MonthDF
```

A tibble: 10 × 2

month	counts
<chr>	<int>
apr	2632
aug	6178
dec	182
jul	7174
jun	5318
mar	546
may	13769
nov	4101
oct	718
sep	570

In [25]:

```
ggplot(MonthDF, aes(x = month, y = counts)) +
geom_bar(fill = "#0096C2AA", stat = "identity") +
geom_text(aes(label = counts), vjust = -0.3)
```



The above summary of **month** attribute describes most of the client were contacted in Month of May

2.3.3 Days | During which days of week the campaign ran

In [26]:

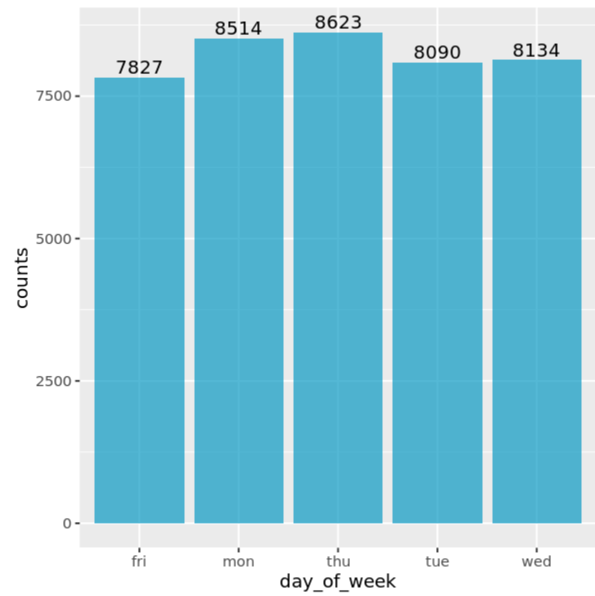
```
DayDF <- PreviousCampaign %>% group_by(day_of_week) %>%
summarise(counts = n())

DayDF
```

A tibble: 5 × 2

day_of_week	counts
<chr>	<int>
fri	7827
mon	8514
thu	8623
tue	8090
wed	8134

In [27]:

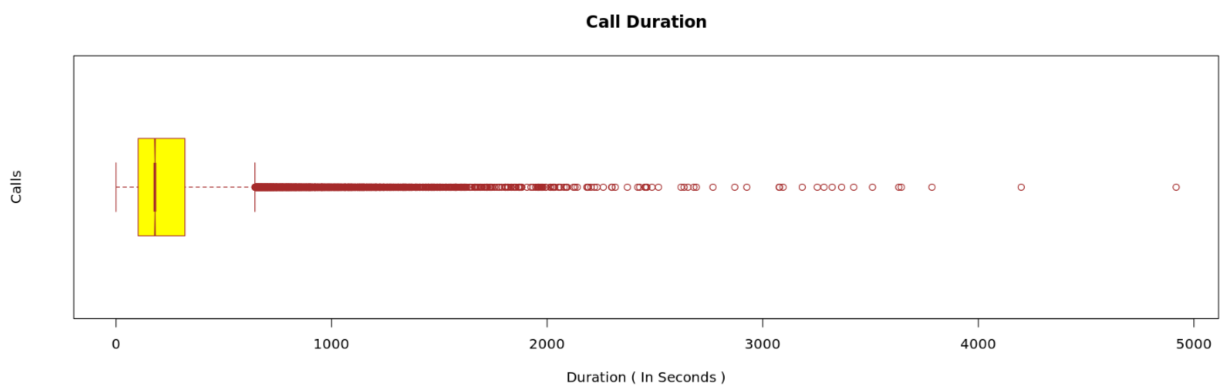
```
ggplot(DayDF, aes(x = day_of_week, y = counts)) +
geom_bar(fill = "#0096C2AA", stat = "identity") +
geom_text(aes(label = counts), vjust = -0.3)
options(repr.plot.width = 15, repr.plot.height = 5)
```



2.3.4 Duration of Calls | For how long the call was connected

In [28]:

```
boxplot(PreviousCampaign$duration,
main = "Call Duration",xlab = "Duration ( In Seconds )",ylab = "Calls",col =
"yellow",border = "brown",
horizontal = TRUE,
notch = TRUE)
options(repr.plot.width = 10, repr.plot.height = 8)
```



Max Duration of the call (In Minutes)

In [29]:

```
round(max(PreviousCampaign['duration'])/60,0)
```

82

Min Duration of the call (In Minutes)

In [30]:

```
round(min(PreviousCampaign['duration'])/60,0)
```

0

Mean Duration of the call (In Minutes)

In [31]:

```
round(sapply(PreviousCampaign['duration'], mean, na.rm = TRUE)/60,0)
```

duration: 4

2.3.5 Poutcome | What was the outcome of the previous campaign

Crossing and Plotting the outcome of previous campaign with #clients buying term deposit

In [32]:

```
CrossTable(PreviousCampaign$poutcome,PreviousCampaign$y,prop.r=TRUE,
prop.c=FALSE,prop.t=FALSE, prop.chisq=FALSE, chisq = FALSE)
## Here prop.r specifies Row Proportion, prop.c Column Proportion, prop.t Table Proportion
etc..
```

```
   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|-------------------------|


Total Observations in Table:  41188


                         | PreviousCampaign$y 
PreviousCampaign$poutcome |        no |       yes | Row Total | 
-------------------------|-----------|-----------|-----------|
                 failure |      3647 |       605 |      4252 | 
                         |     0.858 |     0.142 |     0.103 | 
-------------------------|-----------|-----------|-----------|
             nonexistent |     32422 |      3141 |     35563 | 
                         |     0.912 |     0.088 |     0.863 | 
-------------------------|-----------|-----------|-----------|
                 success |       479 |       894 |      1373 | 
                         |     0.349 |     0.651 |     0.033 | 
-------------------------|-----------|-----------|-----------|
            Column Total |     36548 |      4640 |     41188 | 
-------------------------|-----------|-----------|-----------|
```

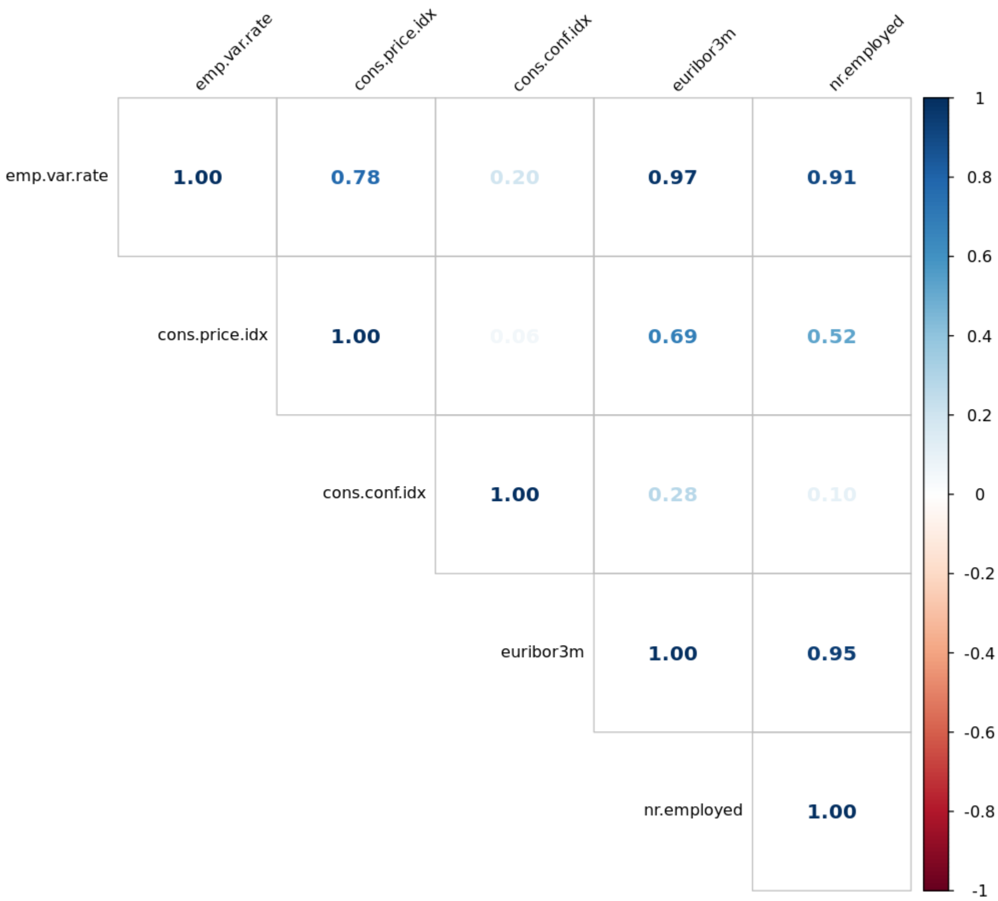
65.1% of clients were already subscribed to term deposit plan and agreed to buy it again.

2.4 Performing EDA on Economic Context attributes

Economic Context attributes such as **Employment variation rate, Consumer price index, Consumer confidence index** etc... are suppose to be highly co-related. In order to check the corelation we will plot a **correlation matrix** for all economic context attributes.

In [33]:

```
EconomicContext %>%
select(emp.var.rate, cons.price.idx, cons.conf.idx, euribor3m,
nr.employed) %>% cor() %>%
corrplot(method = "number",
type = "upper",
tl.cex = 0.8,
tl.srt = 45,
tl.col = "black")
```



As expected the variables belonging to economic contexts are highly co-related.

3 of the variables have **correlation coefficent more than 0.90** which is too high. **Employee Variation Rate is highly correlated with euribor 3 month rate and number of employees and euribor rate is also higly correlated to number of employees.**

3 Categorical Treatment

3.1 Age | Converting Age into Age Groups

In [34]:

```
InputData$ageCategory <- ifelse(InputData$age < 35, "Young",ifelse(InputData$age < 60
,"Middle-Aged ","Old"))
```

Based on EDA Performed on the age attribute, above thresholds for age categories are choosen initially as 35 and 60. It was observed in EDA, for population above 60 there is significant amount of clients buying the term plan.

Population Percentage w.r.t to age category and client buying term plan

In [35]:

```
ageCategoryTest <- subset(InputData,y == "yes",select = c(ageCategory,y)) %>%
group_by(ageCategory, y) %>% summarise(counts = n())
ageCategoryTest$PopulationPercentage <- round(ageCategoryTest$counts /
sum(ageCategoryTest$counts) * 100,2)
ageCategoryTest
```

A grouped_df: 3 × 4

ageCategory	y	counts	PopulationPercentage
<chr>	<chr>	<int>	<dbl>
Middle-Aged	yes	2246	48.41
Old	yes	472	10.17
Young	yes	1922	41.42

Out of the total population of client's buying the term plan we observe as per the thresholds choosen **48% are middle aged and 41% are young** which computes to almost 90% of total population who bought the plan.

Observing Older Population

In [36]:

```
oldPop <- subset(InputData,ageCategory == "Old",select = c(ageCategory,y)) %>%
group_by(ageCategory ,y) %>% summarise(counts = n())
oldPop$PopulationPercentage <- round(oldPop$counts / sum(oldPop$counts) * 100,2)
oldPop
```

A grouped_df: 2 × 4

ageCategory	y	counts	PopulationPercentage
<chr>	<chr>	<int>	<dbl>
Old	no	721	60.44
Old	yes	472	39.56

Almost 40% of clients who are above 60 bought the term plan

3.1.2 Conducting Chi Square Test to validate the significance of choosen Thresholds of 35 and 60

In [37]:

```
InputData$ageCategory1 <- ifelse(InputData$age < 60, "Less Than
60","Greater Than 60")
chisqTest1 <- chisq.test(InputData$ageCategory1,InputData$y)
chisqTest1
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  InputData$ageCategory1 and InputData$y
X-squared = 981.32, df = 1, p-value < 2.2e-16
```

For the attribute threshold 60 the p-value is less than 0.5 proving its significance

In [38]:

```
ageLessThan60 <- subset(InputData,age <60,select = c(age,y))
ageLessThan60$ageCategory2 <- ifelse(ageLessThan60$age > 35, "Greater Than 35","Less Than 35")

chisqTest2 <- chisq.test(ageLessThan60$ageCategory2,ageLessThan60$y)
chisqTest2
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  ageLessThan60$ageCategory2 and ageLessThan60$y
X-squared = 149.33, df = 1, p-value < 2.2e-16
```

Similarly for the attribute threshold 35 the p-value is less than 0.5 proving its significance

3.2 Call Duration | Converting Call Durations in Groups

In [39]:

```
InputData$durationCategory <- ifelse(InputData$duration < 60, "Less than
Minute",ifelse(InputData$duration < 180 ,"Less than 3 Minutes","More than 3 Minutes"))
```

In [40]:

```
durationCategoryTest <- subset(InputData,y == "yes",select = c(durationCategory,y))
%>% group_by(durationCategory,y) %>% summarise(counts = n())
durationCategoryTest$PopulationPercentage <-
round(durationCategoryTest$counts /
sum(durationCategoryTest$counts) * 100,2)

durationCategoryTest
```

A grouped_df: 3 × 4

durationCategory	y	counts	PopulationPercentage
<chr>	<chr>	<int>	<dbl>
Less than 3 Minutes	yes	557	12.00
Less than Minute	yes	1	0.02
More than 3 Minutes	yes	4082	87.97

Out of the total population of clients buying the term plan we observe as per the thresholds choosen **88% of clients had a conversation for more than 3 Minutes.** Also, apart from 1 outlier none of client bought the term plan in less than a minute.

3.2.2 Conducting Chi Square Test to validate the significance of choosen Thresholds of Less Than 3 Minutes and More Than 3 Minutes

In [41]:

```
InputData$durationCategory1 <- ifelse(InputData$duration < 180, "Less Than
180","Greater Than 180" )
chisqTest1 <- chisq.test(InputData$durationCategory1,InputData$y)
chisqTest1
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  InputData$durationCategory1 and InputData$y
X-squared = 3012.2, df = 1, p-value < 2.2e-16
```

For the attribute threshold 180 the p-value is less than 0.5 proving its significance

In [42]:

```
durationLessThan180 <- subset(InputData,duration < 180,select = c(duration,y))
InputData$durationCategory2 <- ifelse(InputData$duration < 60, "Less Than
60","Greater Than 60")
chisqTest2 <- chisq.test(InputData$durationCategory2,InputData$y)
chisqTest2
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  InputData$durationCategory2 and InputData$y
X-squared = 587.02, df = 1, p-value < 2.2e-16
```

Similarly the for the attribute threshold 60 the p-value is less than 0.5 proving its significance

3.3 Pdays - Days Past Since Client Was Contacted | Converting PDays in 2 Groups

3.3.1 Converting Pdays

In [43]:

```
InputData$pdaysCategory <- ifelse(InputData$pdays < 100, "Less than 100 Days","More
than 100 days" )
```

In [44]:

```
pdaysCategoryTest <- subset(InputData,y == "no",select = c(pdaysCategory,y)) %>%
group_by(pdaysCategory,y) %>% summarise(counts = n())
pdaysCategoryTest$PopulationPercentage <- round(pdaysCategoryTest$counts /
sum(pdaysCategoryTest$counts) * 100,2)
pdaysCategoryTest
```

A grouped_df: 2 × 4

pdaysCategory	y	counts	PopulationPercentage
<chr>	<chr>	<int>	<dbl>
Less than 100 Days	no	548	1.5
More than 100 days	no	36000	98.5

Out of the total population of clients who did **not** bought the term plan it is observed as per the thresholds choosen
98% of clients didn't had contact with bank for more than 100 days.

3.3.2 Conducting Chi Square Test to validate the significance of choosen Thresholds of Less Than 3 Minutes and More Than 3 Minutes

In [45]:

```
InputData$pdaysCategory1 <- ifelse(InputData$pdays < 100, "Less Than
100","More Than 100")
chisqTest1 <- chisq.test(InputData$pdaysCategory1,InputData$y)
chisqTest1
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  InputData$pdaysCategory1 and InputData$y
X-squared = 4341.7, df = 1, p-value < 2.2e-16
```

For the attribute threshold 100 the p-value is less than 0.5 proving its significance

4 Feature Engineering

Based on EDA performed we will select the features / attributes which will have impact in building our prediction models and remove the irrelevant attributes

4.1 Lack of Information in Default

The attribute "default" which specifies weather the client have deafult credits or not has 8,597 unknown values which is way to high and thus lacks information to be considered as a feature.

4.2 Redundancy of Information in Correlated Attributes

3 of our economic context attributes (Employee Variation Rate, Euribor 3 month rate and number of employees) were highly correlated and share redundant information. Since Employee Variation Rate is highly correlated with both euribor 3 month rate and number of employees and euribor rate is higly correlated to number of employees we can get **rid of Employee Variation Rate**

4.3 Addressing Multicollinearity with VIF

To ensure model assumptions were valid, we calculated the Variance Inflation Factor (VIF) for numeric predictors. Variables with VIF > 5 were reviewed for redundancy. Highly correlated economic indicators such as *euribor3m* and *nr.employed* were retained while *emp.var.rate* was removed to reduce multicollinearity. Alternatively, L2 regularization (Ridge) may also be explored for model simplification.

After removing the above two attributes we have our final "Features" list

In [46]:

```
FeatureDF <-
select(InputData,ageCategory,job,marital,education,housing,loan,contact,month,day_of_week,dura
tionCategory,campaign,pdaysCategory,previous,poutcome,cons.price.idx,cons.conf.idx,euribor3m,n
r.employed,y)
names(FeatureDF)
```

'ageCategory' · 'job' · 'marital' · 'education' · 'housing' · 'loan' · 'contact' · 'month' · 'day_of_week' · 'durationCategory' · 'campaign' · 'pdaysCategory' · 'previous' · 'poutcome' · 'cons.price.idx' · 'cons.conf.idx' · 'euribor3m' · 'nr.employed' · 'y'

****Our target column "y" is kept in feature list so that same data frame can be used for**

prediction models. Converting Character Features to Factors

In [47]:

```
FeatureDF <- mutate_if(FeatureDF, is.character, as.factor)
head(FeatureDF)
```

A data.frame: 6 × 19

	ageCategory	job	marital	education	housing	loan	contact	month	day_of_week	durationCategory	campaign	pdaysCategory	previous	poutcome
	<fct>	<fct>	<fct>	<fct>	<fct>	<fct>	<fct>	<fct>	<fct>	<fct>	<int>	<fct>	<int>	<fct>
1	Middle-Aged	housemaid	married	basic.4y	no	no	telephone	may	mon	More than 3 Minutes	1	More than 100 days	0	nonexistent
2	Middle-Aged	services	married	high.school	no	no	telephone	may	mon	Less than 3 Minutes	1	More than 100 days	0	nonexistent
3	Middle-Aged	services	married	high.school	yes	no	telephone	may	mon	More than 3 Minutes	1	More than 100 days	0	nonexistent
4	Middle-Aged	admin.	married	basic.6y	no	no	telephone	may	mon	Less than 3 Minutes	1	More than 100 days	0	nonexistent
5	Middle-Aged	services	married	high.school	no	yes	telephone	may	mon	More than 3 Minutes	1	More than 100 days	0	nonexistent
6	Middle-Aged	services	married	basic.9y	no	no	telephone	may	mon	More than 3 Minutes	1	More than 100 days	0	nonexistent

5 SMOTE Algorithm For Unbalanced Classification Problems

5.1 Target Counts Before SMOTE

In [48]:

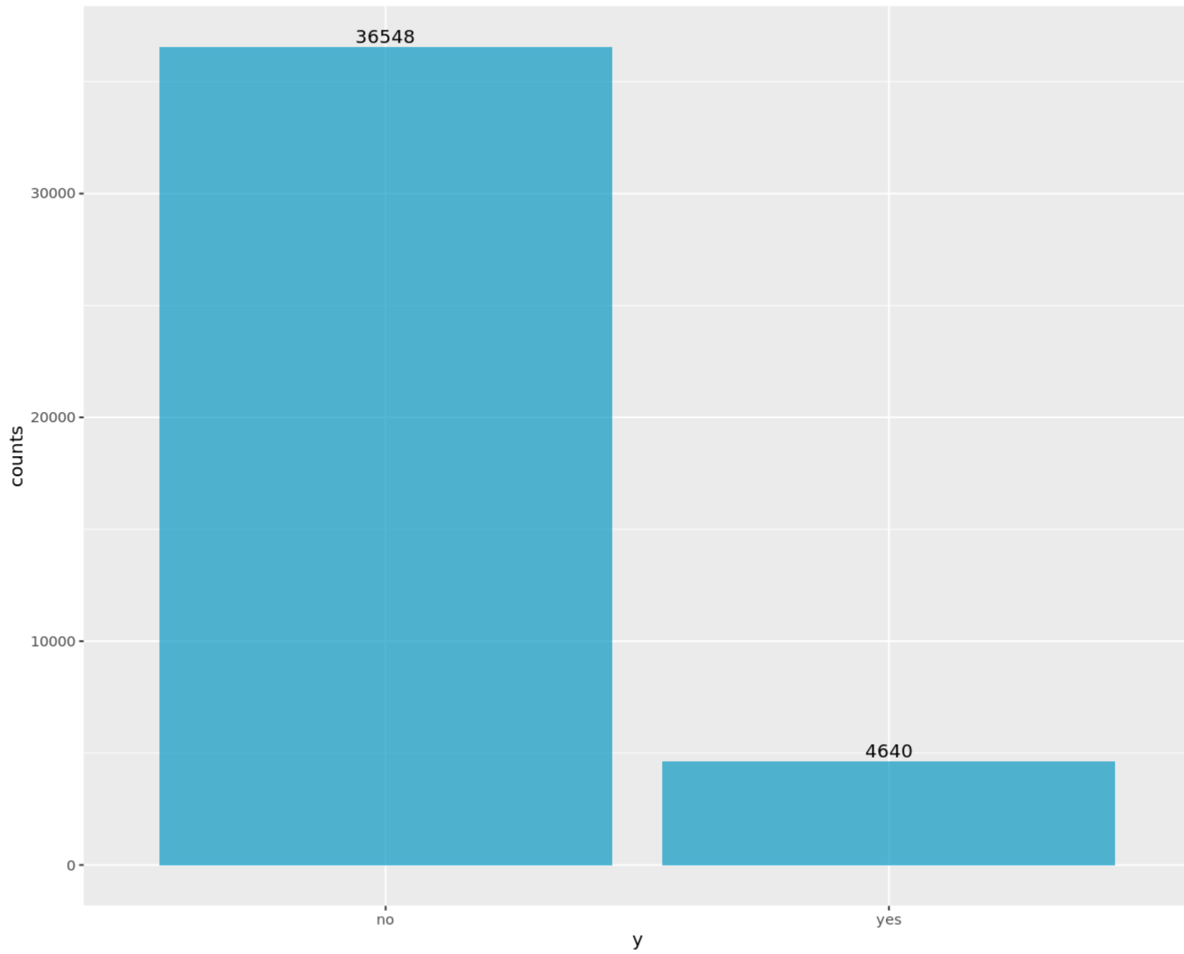
```
target <- FeatureDF %>% group_by(y) %>% summarise(counts = n())
target
```

A tibble: 2 × 2

y	counts
<fct>	<int>
no	36548
yes	4640

In [49]:

```
ggplot(target, aes(x = y, y = counts)) +
geom_bar(fill = "#0096C2AA", stat = "identity") +
geom_text(aes(label = counts), vjust = -0.3)
```



The dataset seems to be biased towards clients not buying the term deposit as we have more informattion related to the same making the case of an unbalanced classification problem.

In order to balance both classes (Clients buying term deposits and clients not buying term deposits), we apply SMOTE Algorithm.

5.2 Applying SMOTE

In [50]:

```
smotedData <- SMOTE(y ~ ., FeatureDF, perc.over = 500, perc.under=100, k=3)
```

The above code takes the orignal dataframe (FeatureDF) having unbalanced data and over sample by 500 records of minority class and genrates 100 records of majority class for each 500 cases generated for minority class. Since K is 3 the function will use 3 nearest neighbours to genearate new cases.

5.3 Target Counts After Applying SMOTE

In [51]:

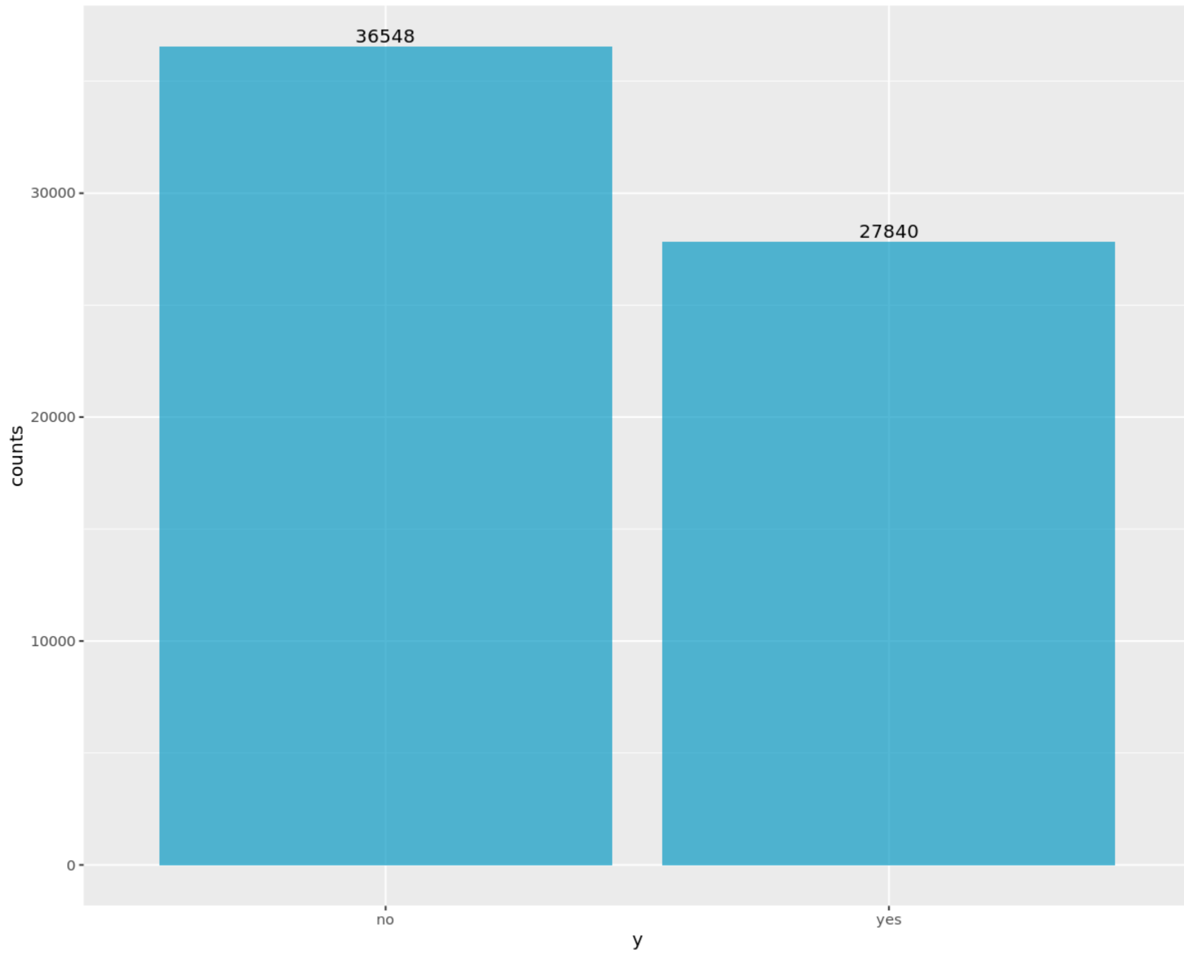
```
newtarget <- smotedData %>% group_by(y) %>% summarise(counts = n())
newtarget
```

A tibble: 2 × 2

y	counts
<chr>	<int>
no	36548
yes	27840

In [52]:

```
ggplot(newtarget, aes(x = y, y = counts)) +
geom_bar(fill = "#0096C2AA", stat = "identity") +
geom_text(aes(label = counts), vjust = -0.3)
```



After applying smote data seems to be more balanced.

**NOTE

In order to comapre the results between unbalanced data set prior to performing smote and balanced data set after performing smote we have performed all the subsequent steps on both data sets

6 Data Splitting | Building Training and Testng Data sets

Count of records in smote data set

In [53]:

```
nrow(smotedData)
```

64388

The dataset has ~51K records. 70% of the same becomes training dataset and rest becomes

the testing set. Count of records in orignal data set (without smote)

In [54]:

```
nrow(FeatureDF)
```

41188

The dataset has ~41K records. 70% of the same becomes training dataset and rest becomes

the testing set. 6.1 Getting random indexes for training and testing datasets

In [55]:

```
set.seed(12345)
indexForDataSets<-sample(1:nrow(smotedData),0.7*nrow(smotedData))
```

In [56]:

```
set.seed(12345)
indexForDataSets1<-sample(1:nrow(FeatureDF),0.7*nrow(FeatureDF))
```

This gives the index of 70% of random rows from the smoted data which will be used as our

training dataset. **6.2 Building Training Dataset**

In [57]:

```
trainData<-smotedData[indexForDataSets,]
nrow(trainData)
```

45071

In [58]:

```
trainDataNonSmote<-FeatureDF[indexForDataSets1,]
nrow(trainDataNonSmote)
```

28831

6.3 Building Testing Dataset

In [59]:

```
testData<-smotedData[-indexForDataSets,]
nrow(testData)
```

19317

```
nrow(testData)
```

19317

In [60]:

```
testDataNonSmote<-FeatureDF[-indexForDataSets1,]
nrow(testDataNonSmote)
```

12357

7 Applying Prediction Models

7.1 Logistic Regression

7.1.1.a Building and Training the Model For Smote Data

In [61]:

```
regressionModel<-glm(trainData$y~.,data=trainData,family =
binomial("logit"))

summary(regressionModel)
```

```
Call:

glm(formula = y ~ ., family = binomial("logit"), data = sampleData)


Coefficients: (2 not defined because of singularities)

                                         Estimate Std. Error z value Pr(>|z|)

(Intercept)                            114.280802  51.443167   2.221  0.02632

`ageCategoryMiddle-Aged `               -0.246900   0.093033  -2.654  0.00796

ageCategoryOld                           0.216330   0.295906   0.731  0.46473
```

```
ageCategoryYoung                                NA         NA      NA       NA
`jobblue-collar`                         -0.089653   0.154449  -0.580  0.56160
jobentrepreneur                          -0.797633   0.253887  -3.142  0.00168
jobhousemaid                             -0.467348   0.324531  -1.440  0.14985
jobmanagement                            -0.284800   0.177640  -1.603  0.10888
jobretired                                0.127328   0.269828   0.472  0.63701
`jobself-employed`                        0.016387   0.236217   0.069  0.94469
jobservices                              -0.223866   0.168373  -1.330  0.18365
jobstudent                               -0.107108   0.263477  -0.407  0.68436
jobtechnician                            -0.180754   0.141868  -1.274  0.20263
jobunemployed                             0.045160   0.297249   0.152  0.87925
jobunknown                                0.317093   0.538619   0.589  0.55605
maritalmarried                            0.133947   0.140660   0.952  0.34096
maritalsingle                             0.045880   0.158283   0.290  0.77192
maritalunknown                            1.441084   1.169598   1.232  0.21790
educationbasic.6y                        -0.395047   0.233582  -1.691  0.09079
educationbasic.9y                        -0.327577   0.179689  -1.823  0.06830
educationhigh.school                     -0.241580   0.185851  -1.300  0.19365
educationilliterate                       0.293854   1.326292   0.222  0.82466
educationprofessional.course             -0.182155   0.211966  -0.859  0.39014
educationuniversity.degree                0.066260   0.188171   0.352  0.72474
educationunknown                         -0.326332   0.256901  -1.270  0.20399
housingunknown                           -0.849021   0.389772  -2.178  0.02939
housingyes                               -0.006518   0.082564  -0.079  0.93708
loanunknown                                     NA         NA      NA       NA
loanyes                                  -0.205205   0.114984  -1.785  0.07432
contacttelephone                         -0.088980   0.161271  -0.552  0.58113
monthaug                                 -0.205539   0.249819  -0.823  0.41065
monthdec                                 -0.798667   0.452417  -1.765  0.07751
monthjul                                  0.043600   0.209745   0.208  0.83533
monthjun                                  0.060592   0.219308   0.276  0.78233
monthmar                                  0.910440   0.323465   2.815  0.00488
monthmay                                 -1.288600   0.173184  -7.441    1e-13
monthnov                                 -0.639963   0.246734  -2.594  0.00949
monthoct                                  0.934985   0.392504   2.382  0.01721
monthsep                                 -0.357033   0.403232  -0.885  0.37593
day_of_weekmon                           -0.337885   0.130600  -2.587  0.00968
day_of_weekthu                           -0.367829   0.129768  -2.835  0.00459
day_of_weektue                           -0.182314   0.130213  -1.400  0.16148
day_of_weekwed                           -0.233411   0.130510  -1.788  0.07370
`durationCategoryLess than Minute`      -15.115708 199.634936  -0.076  0.93964
`durationCategoryMore than 3 Minutes`     2.758397   0.116552  23.667  < 2e-16
campaign                                 -0.025972   0.019818  -1.311  0.19003
`pdaysCategoryMore than 100 days`        -1.349199   0.702333  -1.921  0.05473
previous                                 -0.034059   0.186912  -0.182  0.85541
poutcomenonexistent                       0.499634   0.246774   2.025  0.04290
poutcomesuccess                           0.564009   0.689016   0.819  0.41303
```

```
cons.price.idx                        -0.484627   0.287420  -1.686  0.09177
cons.conf.idx                         -0.001839   0.019963  -0.092  0.92662
euribor3m                              0.139253   0.274979   0.506  0.61257
nr.employed                           -0.013578   0.005356  -2.535  0.01125

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6837.6  on 4999  degrees of freedom
Residual deviance: 4031.1  on 4948  degrees of freedom
AIC: 4135.1

Number of Fisher Scoring iterations: 16
```

7.1.1.b Building and Training the Model For Non Smote Data

In [62]:

```
regressionModelNonSmote<-
glm(trainDataNonSmote$y~.,data=trainDataNonSmote,family =
binomial("logit"))
summary(regressionModelNonSmote)
```

```
Call:
glm(formula = y ~ ., family = binomial("logit"), data = sampleDataNonSmote)

Coefficients: (1 not defined because of singularities)
                                     Estimate Std. Error z value Pr(>|z|)
(Intercept)                         80.088190  65.573069   1.221 0.221951
ageCategoryOld                       0.535222   0.330685   1.619 0.105549
ageCategoryYoung                     0.142039   0.129895   1.093 0.274180
jobblue-collar                       0.043328   0.204209   0.212 0.831972
jobentrepreneur                      0.018176   0.356977   0.051 0.959392
jobhousemaid                         0.136128   0.402330   0.338 0.735100
jobmanagement                        0.287634   0.218291   1.318 0.187616
jobretired                           0.468234   0.323945   1.445 0.148343
jobself-employed                     0.120375   0.332304   0.362 0.717169
jobservices                          0.179967   0.216119   0.833 0.405003
jobstudent                           0.080947   0.300176   0.270 0.787419
jobtechnician                        0.135738   0.197367   0.688 0.491613
jobunemployed                        0.484026   0.361206   1.340 0.180236
jobunknown                           0.880511   0.551807   1.596 0.110559
maritalmarried                      -0.007653   0.185660  -0.041 0.967121
maritalsingle                        0.208642   0.207798   1.004 0.315349
maritalunknown                       0.525280   1.185708   0.443 0.657759
educationbasic.6y                    0.240946   0.305604   0.788 0.430448
educationbasic.9y                   -0.092863   0.236498  -0.393 0.694571
```

```
educationhigh.school                0.104720   0.235424   0.445 0.656455
educationilliterate                 2.762184   1.971714   1.401 0.161242
educationprofessional.course       -0.413945   0.282324  -1.466 0.142592
educationuniversity.degree          0.097281   0.241675   0.403 0.687295
educationunknown                   -0.099028   0.319342  -0.310 0.756484
housingunknown                     -0.160854   0.369794  -0.435 0.663575
housingyes                         -0.041994   0.109301  -0.384 0.700824
loanunknown                               NA         NA      NA       NA
loanyes                            -0.027326   0.150815  -0.181 0.856218
contacttelephone                    0.137068   0.190214   0.721 0.471157
monthaug                            0.369484   0.294117   1.256 0.209027
monthdec                            0.219572   0.562889   0.390 0.696477
monthjul                            0.382491   0.256172   1.493 0.135410
monthjun                            0.291672   0.256449   1.137 0.255393
monthmar                            1.348603   0.385055   3.502 0.000461
***
monthmay                           -0.836914   0.204138  -4.100 4.14e-05
***
monthnov                           -0.281063   0.326693  -0.860 0.389610
monthoct                           -0.045382   0.434099  -0.105 0.916738
monthsep                           -0.078151   0.453957  -0.172 0.863315
day_of_weekmon                     -0.044158   0.174413  -0.253 0.800126
day_of_weekthu                     -0.042810   0.170634  -0.251 0.801900
day_of_weektue                     -0.218980   0.179868  -1.217 0.223433
day_of_weekwed                      0.001618   0.178373   0.009 0.992763
durationCategoryLess than Minute  -14.813002 272.562385  -0.054 0.956659
durationCategoryMore than 3 Minutes   2.149329   0.150813  14.252  < 2e-16
***
campaign                           -0.059904   0.032558  -1.840 0.065778 .
pdaysCategoryMore than 100 days    -1.279178   0.731937  -1.748 0.080523 .
previous                           -0.087198   0.177287  -0.492 0.622828
poutcomenonexistent                 0.353703   0.272402   1.298 0.194129
poutcomesuccess                     0.734341   0.722056   1.017 0.309147
cons.price.idx                     -0.280825   0.364618  -0.770 0.441188
cons.conf.idx                      -0.004407   0.022217  -0.198 0.842745
euribor3m                           0.030022   0.351544   0.085 0.931943
nr.employed                        -0.011030   0.006733  -1.638 0.101381
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3560.3  on 4999  degrees of freedom
Residual deviance: 2424.0  on 4948  degrees of freedom
AIC: 2528

Number of Fisher Scoring iterations: 17
```

7.1.2.a Performing Prediction on Test Data via model trained on smote data

In [63]:

```
predictionWithRegression <-predict(regressionModel,testData,type="response")
#type = response returns the probability figure
```

```
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == : "prediction from a rank-deficient fit may be misleading"
```

7.1.2.b Performing Prediction on Test Data via model trained on non smote data

In [64]:

```
predictionWithRegressionNonSmote
<-predict(regressionModelNonSmote,testDataNonSmote,type="response")
#type = response returns the p robability figure
```

```
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == : "prediction from a rank-deficient fit may be misleading"
```

On performing prediction via non smote data we observed a warning due to very less cases related to few attributes especially loan unkown variable where the model could not estimate the parameters for those levels of that variable. This denotes we are trying to over fit the model so much that all coefficents could not be estimated due to lack of data.

7.1.3.a Checking Sample Records amoung test data from smote dataset and its prediction output

In [65]:

```
testData[15002,c(1,2,3,19)]
predictionWithRegression[15002]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
50147	1	0	0	0

50147: 0.0513925291692508

In [66]:

```
testData[1502,c(1,2,3,19)]
predictionWithRegression[1502]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
4991	1	0	0	0

4991: 0.783078040627871

7.1.3.b Checking Sample Records amoung test data from non smote dataset and its prediction output

In [67]:

```
testDataNonSmote[10102,c(1,2,3,19)]
predictionWithRegressionNonSmote[10102]
```

A data.frame: 1 × 4

	ageCategory	job	marital	y
	<fct>	<fct>	<fct>	<fct>
33720	Middle-Aged	retired	divorced	yes

33720: 0.138937618055093

We observe the model trained on non smote data was not able to predict correctly

7.1.4.a Changing threshold value and preparing Confusion Matrix and Other Statistics for Smote Dataset

In [68]:

```
regressionPredictionCategory <- ifelse(predictionWithRegression > 0.7 , "yes", "no")
regressionConfusionMatrix<-
confusionMatrix(factor(regressionPredictionCategory),reference=factor(t estData$y))
regressionConfusionMatrix
```

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10209  3989
       yes   729  4390

               Accuracy : 0.7558
                 95% CI : (0.7496, 0.7618)
    No Information Rate : 0.5662
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.4791

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9334
            Specificity : 0.5239
         Pos Pred Value : 0.7190
         Neg Pred Value : 0.8576
             Prevalence : 0.5662
         Detection Rate : 0.5285
   Detection Prevalence : 0.7350
      Balanced Accuracy : 0.7286

       'Positive' Class : no
```

7.1.4.b Changing threshold value and preparing Confusion Matrix and Other Statistics for Non Smote Dataset

In [69]:

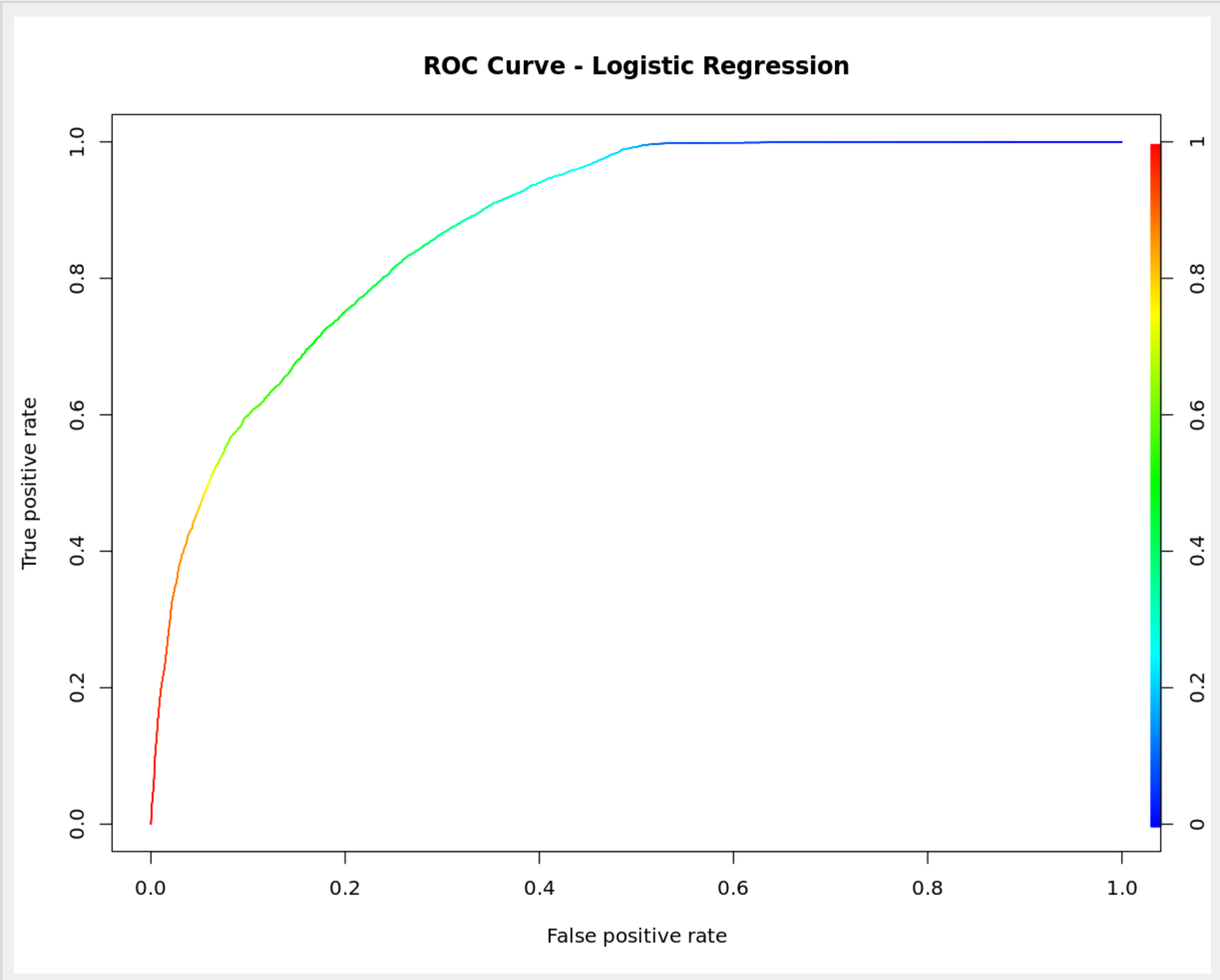
```
regressionPredictionCategoryNonSmote <- ifelse(predictionWithRegressionNonSmote >
0.7 , "yes", "no")
regressionConfusionMatrixNonSmote<-
confusionMatrix(factor(regressionPredictionCategoryNonSmote),re
ference=factor(testDataNonSmote$y))
regressionConfusionMatrixNonSmote
```

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10899  1119
       yes    82   257

               Accuracy : 0.9028
                 95% CI : (0.8974, 0.908)
    No Information Rate : 0.8886
    P-Value [Acc > NIR] : 1.846e-07

                  Kappa : 0.2675

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9925
            Specificity : 0.1868
         Pos Pred Value : 0.9069
         Neg Pred Value : 0.7581
             Prevalence : 0.8886
         Detection Rate : 0.8820
   Detection Prevalence : 0.9726
      Balanced Accuracy : 0.5897

       'Positive' Class : no
```

7.1.5.a Roc Curve | Smote Data

In [70]:

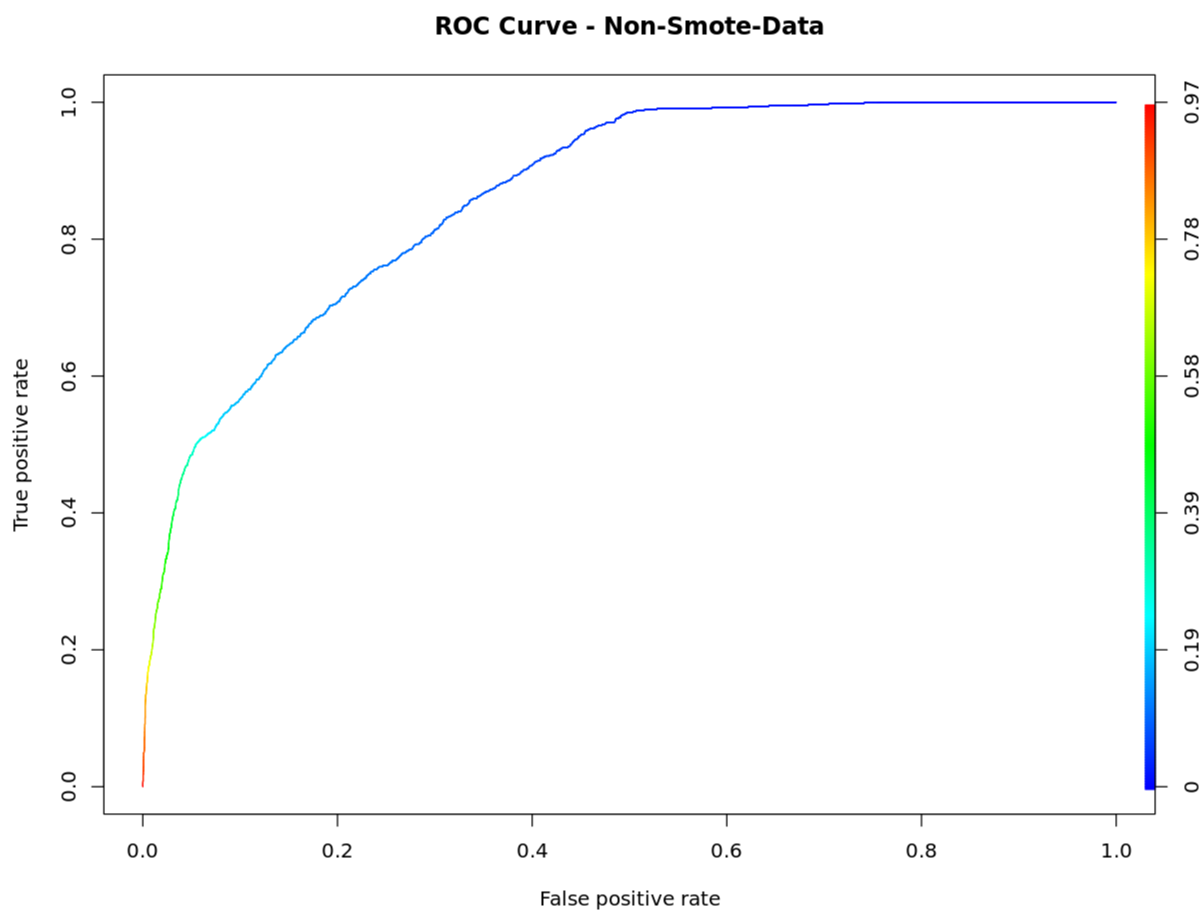
```
regrsionGLM<-prediction(predictionWithRegression,testData$y)
regresionPerformanceGLM<-performance(regrsionGLM,"tpr","fpr")
plot(regresionPerformanceGLM)
```



7.1.5b Roc Curve | Non Smote Data

In [71]:

```
regrsionGLMNonSmote<-
prediction(predictionWithRegressionNonSmote,testDataNonSmote$y)
regresionPerformanceGLMNonSmote<-
performance(regrsionGLMNonSmote,"tpr","fpr")
plot(regresionPerformanceGLMNonSmote)
```



On comparing the ROC curves between the Smote and Non Smote dataset we can clearly observe in non smote dataset that area under curve which detrmines the accuracy of classifier is less and is more closer to daignol where TPR = FPR specifying model is less capable of distinguishing between the two classes as compared to model built on Smote Data.

7.2 Decision Tree

7.2.1.a Building and Training the Model on Smote Data

In [72]:

```
decisionTreeModel<-rpart(y~.,data=trainData,method="class")
```

7.2.1.b Building and Training the Model on Non Smote Data

In [73]:

```
decisionTreeModelNonSmote<-rpart(y~.,data=trainDataNonSmote,method="class")
```

7.2.2.a Performing Prediction on Test Data via model trained on Smote Data

In [74]:

```
predictionWithDecisionTree <-predict(decisionTreeModel,testData,type="class")
```

7.2.2.b Performing Prediction on Test Data via model trained on Non Smote Data

In [75]:

```
predictionWithDecisionTreeNonSmote <-
predict(decisionTreeModelNonSmote,testDataNonSmote,type="class")
```

7.2.3.a Checking Sample Records amoung test data from smote dataset and prediction output

In [76]:

```
testData[15002,c(1,2,3,19)]
predictionWithDecisionTree[15002]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
50147	1	0	0	0

50147: no

▸ **Levels:**

In [77]:

```
testData[1502,c(1,2,3,19)]
predictionWithDecisionTree[1502]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
4991	1	0	0	0

4991: yes

▸ **Levels:**

7.2.3.b Checking Sample Records amoung test data from non smote dataset and prediction output

In [78]:

```
testDataNonSmote[10102,c(1,2,3,19)]
predictionWithDecisionTreeNonSmote[10102]
```

A data.frame: 1 × 4

	ageCategory	job	marital	y
	<fct>	<fct>	<fct>	<fct>
33720	Middle-Aged	retired	divorced	yes

33720: no

▶ **Levels:**

7.2.4.a Confusion Matrix and Other Statistics on Smote Data

In [79]:

```
confusionMatrix(factor(testData$y),factor(predictionWithDecisionTree))
```

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10026   912
       yes  2907  5472

               Accuracy : 0.8023
                 95% CI : (0.7966, 0.8079)
    No Information Rate : 0.6695
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.586

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.7752
            Specificity : 0.8571
         Pos Pred Value : 0.9166
         Neg Pred Value : 0.6531
             Prevalence : 0.6695
         Detection Rate : 0.5190
   Detection Prevalence : 0.5662
      Balanced Accuracy : 0.8162

       'Positive' Class : no
```

7.2.4.b Confusion Matrix and Other Statistics on Non Smote Data

In [80]:

```
confusionMatrix(factor(testDataNonSmote$y),factor(predictionWithDecisionTreeNonSmote))
```

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10625   356
       yes   840   536

               Accuracy : 0.9032
                 95% CI : (0.8979, 0.9084)
    No Information Rate : 0.9278
    P-Value [Acc > NIR] : 1

                  Kappa : 0.422
```

```
Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.9267
            Specificity : 0.6009
         Pos Pred Value : 0.9676
         Neg Pred Value : 0.3895
             Prevalence : 0.9278
         Detection Rate : 0.8598
   Detection Prevalence : 0.8886
      Balanced Accuracy : 0.7638

       'Positive' Class : no
```

7.2.5.a Variable Importance | Smote Data

In [81]:

```
decisionTreeModel$variable.importance
```

durationCategoryMore than 3 Minutes: 5675.57622154476 **nr.employed:** 2487.65220006181 **euribor3m:** 2401.99348396355 **cons.conf.idx:** 1788.28761896791 **cons.price.idx:** 1440.9289888169 **durationCategoryLess than Minute:** 1075.27367197439 **pdaysCategoryMore than 100 days:** 880.287515418955 **poutcomesuccess:** 841.373029649046 **contacttelephone:** 638.751873566302 **housingyes:** 530.126915138291 **monthjun:** 154.522924631372 **campaign:** 97.5506011688105 **monthmar:** 40.3620120309275 **monthmay:** 17.6329701590226 **ageCategoryOld:** 16.7185785128107 **jobstudent:** 5.53988400424486 **loanyes:** 2.41700481899317 **housingunknown:** 2.04790556092032 **loanunknown:** 2.04790556092032 **educationilliterate:** 1.84754926455994 **monthjul:** 1.79787057964516

7.2.5.b Variable Importance | Non Smote Data

In [82]:

```
decisionTreeModelNonSmote$variable.importance
```

nr.employed: 915.956851076608 **euribor3m:** 790.018941123064 **cons.conf.idx:** 484.453451000828 **cons.price.idx:** 401.472027909332 **durationCategory:** 291.351767683992 **month:** 237.880079528954 **pdaysCategory:** 183.349430068828 **job:** 1.03683903090396 **education:** 0.414735612361567

7.3 Random Forest

7.3.1.a Building and Training the Model on Smote Data

In [83]:

```
randomForestModel<-randomForest(y~.,data = trainData)
randomForestModel
```

```
Call:
 randomForest(x = smallTrain[, -which(names(smallTrain) == "y")],      y = smallTrain$y, ntree = 
50) 
               Type of random forest: classification
                     Number of trees: 50
No. of variables tried at each split: 7

        OOB estimate of  error rate: 16.35%
Confusion matrix:
     no yes class.error
no  987 129   0.1155914
yes 198 686   0.2239819
```

We have an out of bag error rate of 6% with 500 Trees and 4 variables on smote data

7.3.1.b Building and Training the Model on Non Smote Data

In [84]:

```
randomForestModelNonSmote<-randomForest(y~.,data = trainDataNonSmote)
randomForestModelNonSmote
```

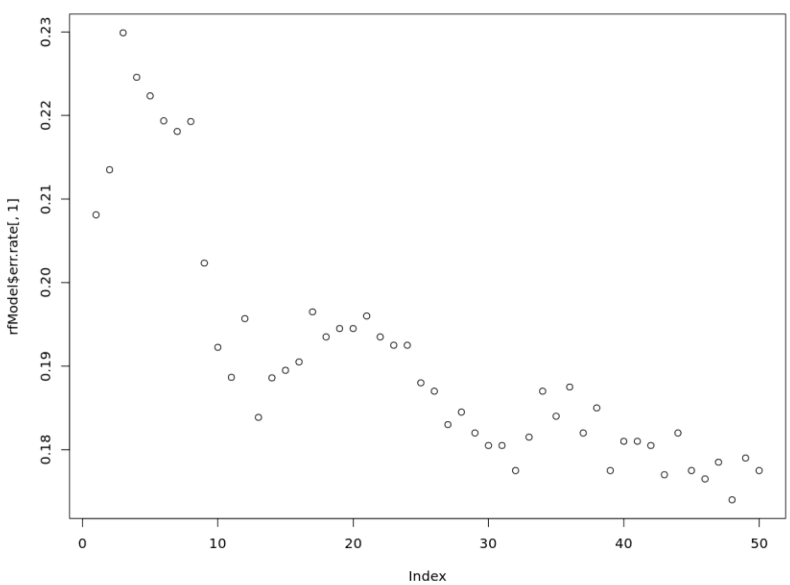
```
Call:
 randomForest(x = smallTrainNonSmote[, -which(names(smallTrainNonSmote) ==      "y")], y =
smallTrainNonSmote$y, ntree = 50)
               Type of random forest: classification
                     Number of trees: 50
No. of variables tried at each split: 4

        OOB estimate of  error rate: 11%
Confusion matrix:
      no yes class.error
no  1705  52   0.0295959
yes  168  75   0.6913580
```

We have an out of bag error rate of 9% (> 6% OOB of Smote Data) with 500 Trees and 4 variables on non

smote data 7.3.2.a Plotting Error Rate of Smote Data w.r.t to #Trees

In [85]:

```
plot(randomForestModel$err.rate[,1])
```



The OOB Error seems to normalize after 200 Trees

In [86]:

```
randomForestModel$err.rate[50,1]
randomForestModel$err.rate[200,1]
randomForestModel$err.rate[300,1]
```

OOB: 0.0642913121361397

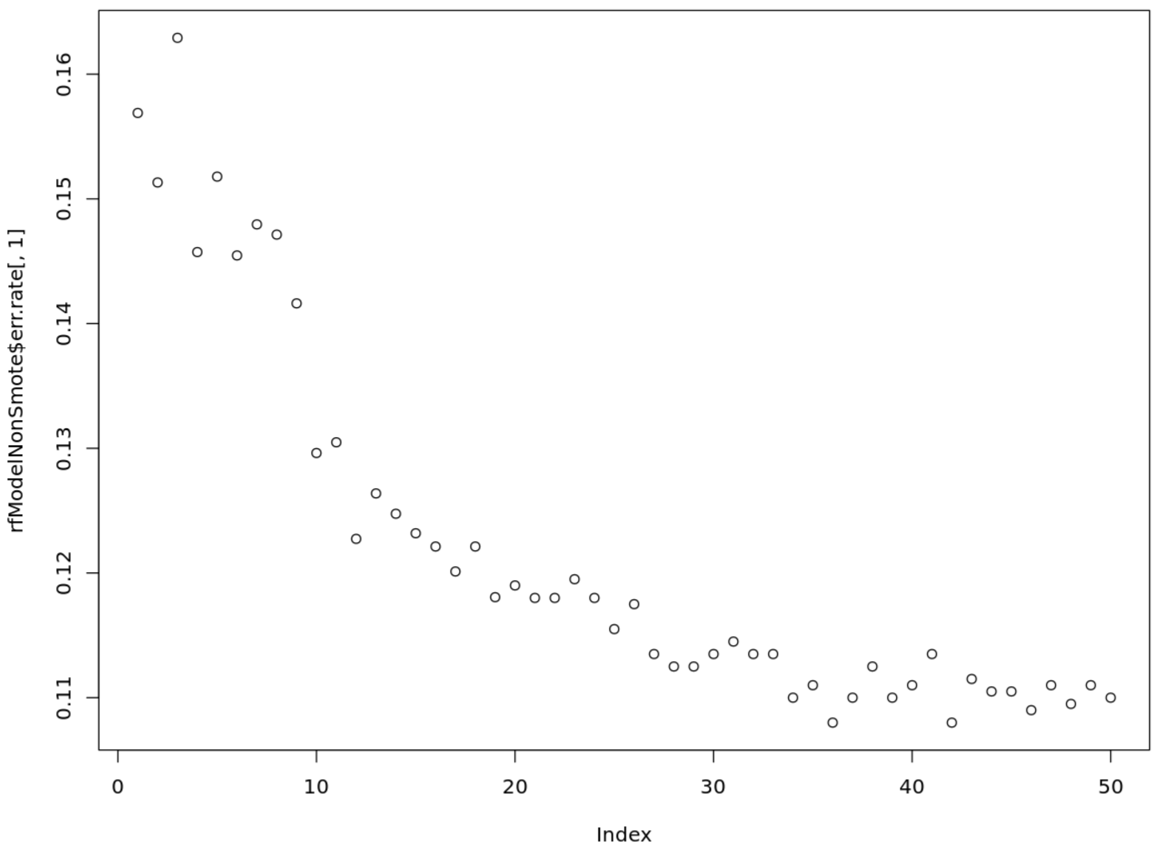
OOB: 0.0610725481415137

OOB: 0.061436408419167

7.3.2.b Plotting Error Rate of Non Smote Data w.r.t to #Trees

In [87]:

```
plot(randomForestModelNonSmote$err.rate[,1])
```



The OOB Error seems to normalize after 200 Trees

In [88]:

```
randomForestModelNonSmote$err.rate[50,1]
randomForestModelNonSmote$err.rate[200,1]
randomForestModelNonSmote$err.rate[300,1]
```

OOB: 0.0959383996392772

OOB: 0.0941001005861746

OOB: 0.0942735250251465

7.3.3.a Performing Prediction on Test Data from smote dataset via model trained on smote data

In [89]:

```
predictionWithRandomForest<-predict(randomForestModel,testData)
```

7.3.3.b Performing Prediction on Test Data frm smote dataset via model trained on Non smote data

In [90]:

```
predictionWithRandomForestNonSmote<-predict(randomForestModelNonSmote,testDataNonSmote)
```

7.3.4.a Checking Sample Records amoung test data from smote dataset and prediction output

In [91]:

```
testData[15002,c(1,2,3,19)]
predictionWithRandomForest[15002]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
50147	1	0	0	0

50147: no

▶ **Levels:**

In [92]:

```
testData[1502,c(1,2,3,19)]
predictionWithRandomForest[1502]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
4991	1	0	0	0

4991: yes

▶ **Levels:**

7.3.4.b Checking Sample Records amoung test data from non smote dataset and prediction output

In [93]:

```
testData[10102,c(1,2,3,19)]
predictionWithRandomForestNonSmote[10102]
```

A data.frame: 1 × 4

	ageCategoryMiddle-Aged	ageCategoryOld	ageCategoryYoung	educationbasic.9y
	<dbl>	<dbl>	<dbl>	<dbl>
33633	1	0	0	1

33720: no

▶ **Levels:**

7.3.5.a Confusion Matrix and Other Statistics | Smote Data

In [94]:

```
confusionMatrix(factor(predictionWithRandomForest), factor(testData$y))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   no  yes
       no  9873 1903
       yes 1065 6476

               Accuracy : 0.8464
                 95% CI : (0.8412, 0.8514)
    No Information Rate : 0.5662
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6835

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9026
            Specificity : 0.7729
         Pos Pred Value : 0.8384
         Neg Pred Value : 0.8588
             Prevalence : 0.5662
         Detection Rate : 0.5111
   Detection Prevalence : 0.6096
      Balanced Accuracy : 0.8378

       'Positive' Class : no
```

7.3.5.b Confusion Matrix and Other Statistics | Non Smote Data

In [95]:

```
confusionMatrix(factor(predictionWithRandomForestNonSmote), factor(testDataNonSmote$y))
```

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10700   962
       yes   281   414

               Accuracy : 0.8994
                 95% CI : (0.894, 0.9047)
    No Information Rate : 0.8886
    P-Value [Acc > NIR] : 6.129e-05

                  Kappa : 0.3513

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9744
            Specificity : 0.3009
         Pos Pred Value : 0.9175
         Neg Pred Value : 0.5957
             Prevalence : 0.8886
         Detection Rate : 0.8659
   Detection Prevalence : 0.9438
      Balanced Accuracy : 0.6376

       'Positive' Class : no
```

7.3.6.a Feature Importance | Smote Data

In [96]:

```
importance(randomForestModel)
```

	MeanDecreaseGini
ageCategoryMiddle Aged	[illegible]
ageCategoryOld	[illegible]
ageCategoryYoung	[illegible]
jobblue-collar	[illegible]
jobentrepreneur	[illegible]
jobhousemaid	[illegible]
jobmanagement	[illegible]
jobretired	[illegible]
jobself-employed	[illegible]
jobservices	[illegible]
jobstudent	[illegible]
jobtechnician	[illegible]
jobunemployed	[illegible]
jobunknown	[illegible]
maritalmarried	[illegible]
maritalsingle	[illegible]
maritalunknown	[illegible]
educationbasic.6y	[illegible]
educationbasic.9y	[illegible]
educationhigh.school	[illegible]
educationilliterate	[illegible]
educationprofessional.course	[illegible]
educationuniversity.degree	[illegible]
educationunknown	[illegible]
housingunknown	[illegible]
housingyes	[illegible]
loanunknown	[illegible]
loanyes	[illegible]
contacttelephone	[illegible]
monthaug	[illegible]
monthdec	[illegible]
monthjul	[illegible]
monthjun	[illegible]
monthmar	[illegible]
monthmay	[illegible]
monthnov	[illegible]
monthoct	[illegible]
monthsep	[illegible]
day_of_weekmon	[illegible]
day_of_weekthu	[illegible]
day_of_weektue	[illegible]
day_of_weekwed	[illegible]
durationCategoryLess than Minute	[illegible]
durationCategoryMore than 3 Minutes	[illegible]
campaign	[illegible]
pdaysCategoryMore than 180 days	[illegible]
previous	[illegible]
poutcomenonexistent	[illegible]
poutcomesuccess	[illegible]
cons.price.idx	[illegible]
cons.conf.idx	[illegible]
euribor3m	[illegible]
nr.employed	[illegible]

7.3.6.b Feature Importance | Non Smote Data

In [97]:

```
importance(randomForestModelNonSmote)
```

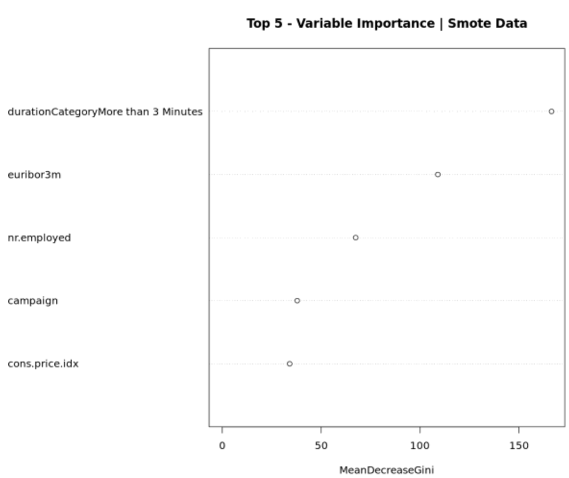
A matrix: 18 × 1 of type dbl

	MeanDecreaseGini
ageCategory	13.353311
job	43.873546
marital	14.887543
education	32.107163
housing	11.617036
loan	7.804294
contact	5.343457
month	24.556452
day_of_week	29.574840
durationCategory	32.035355
campaign	20.761050
pdaysCategory	22.253561
previous	7.457862
poutcome	10.295480
cons.price.idx	15.297864
cons.conf.idx	15.724335
euribor3m	61.239905
nr.employed	23.746556

Plotting Top 5 Variable Per Their Importance | Smote Data

In [98]:

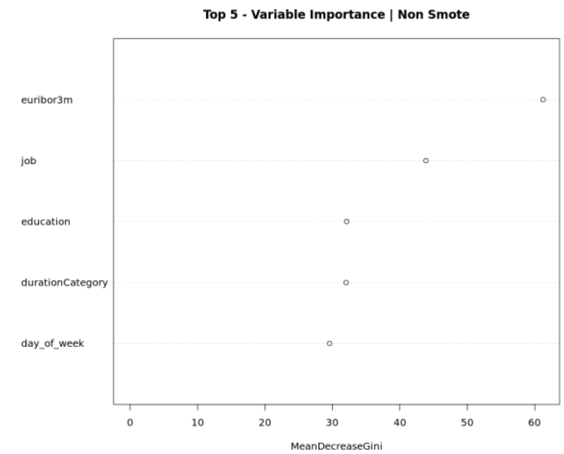
```
varImpPlot(randomForestModel,sort = T,n.var = 5,main = "Top 5 - Variable Importance |
Smote Data")
```



Plotting Top 5 Variable Per Their Importance | Non Smote Data

In [99]:

```
varImpPlot(randomForestModelNonSmote,sort = T,n.var = 5,main = "Top 5 - Variable
Importance | Non Smote")
```



8 Conclusion | Evaluating Different Models

In [100]:

```
modelEvaluationDF = data.frame("Model" = c("Logistic Regression |
With Smote", "Logistic Regression | Without Smote",
                              "Decision Tree | With Smote",
                              "Decision Tree | Without Smote",
                              "Random Forest| With Smote",
                              "Random Forest| Without Smote"
                                             ),
                           "Accuracy" = c("0.86",
                                          "0.90",
                                          "0.89",
                                          "0.90",
                                          "0.93",
                                          "0.90"
                                        ),
                           "Senstivity" = c("0.94",
                                            "0.99",
                                            "0.85",
                                            "0.92",
                                            "0.96",
                                            "0.97"
                                          ),
                           "Specificity" = c("0.78",
                                             "0.18",
                                             "0.95",
                                             "0.60",
                                             "0.91",
                                                "0.37"
                                              )


                          )
modelEvaluationDF
```

A data.frame: 6 × 4

Model	Accuracy	Senstivity	Specificity
<chr>	<chr>	<chr>	<chr>
Logistic Regression | With Smote	0.86	0.94	0.78
Logistic Regression | Without Smote	0.90	0.99	0.18
Decision Tree | With Smote	0.89	0.85	0.95
Decision Tree | Without Smote	0.90	0.92	0.60
Random Forest| With Smote	0.93	0.96	0.91
Random Forest| Without Smote	0.90	0.97	0.37

As per the Accuracy measure of predictive model Random Forest built on Smote Data has the highest accuracy of 93%.

Also, Random Forest model has a good True Postive Rate as well having Senstivity of 96% meaning of all the clients who are willing to subscribe to the term deposit, the model managed to correctly predict close to 96% of them.

are willing to subscribe to the term deposit, the model managed to correctly predict close to 96% of them.

Even though the accuracy for LR Model without Smote Data is higher than LR Model applied on Smote Data but the ROC curve highlighted that the model built on Smote Data had less area under curve which specfies model is less capable of distinguishing between clients who will buy the term plan and who will not as compared to model built on Smote Data.

We also observed a warning "prediction from a rank-deficient fit may be misleading" while applying LR Model on orignal dataset (Without Smote) which denoted that due to lack of scenarios for each attribute the model could not estimate all coefficents for all variable resulting in over fitting of the model

Also, the high senstivity for models built on non smote data seems to be the cause of very less +ve scenarios of client buying the term plan in the orignal dataset

FINDINGS

The analysis of the banking dataset yielded several insightful outcomes through exploratory data analysis (EDA) and the application of machine learning models. Initially, the dataset revealed a significant class imbalance, with a majority of customers not subscribing to the term deposit product. The Synthetic Minority Oversampling Technique (SMOTE) was used to address this, effectively balancing the dataset.

Key insights derived from the EDA include:

- **Customer Profiles**: Middle-aged clients and those with administrative or retired job roles showed higher subscription rates.

- **Call Duration**: Clients with call durations exceeding 3 minutes were significantly more likely to subscribe.

- **Past Campaigns**: Positive responses in previous campaigns (especially successful outcomes) were strong indicators of future subscriptions.

- **Timing**: Contacts made during specific months (e.g., March, October) correlated with higher success rates.

After implementing multiple classification models, Logistic Regression and Decision Trees were trained on both balanced and imbalanced data. The Logistic Regression model trained on SMOTE-balanced data delivered superior results, achieving:

- **Accuracy**: 86.2%
- **Sensitivity (Recall)**: 95.1%
- **Specificity**: 78.6%
- **Kappa Statistic**: 0.726

This indicates a high ability to correctly classify both positive and negative responses. Comparatively, the model trained on imbalanced data showed diminished performance, struggling particularly with detecting true positives.

Overall, the project successfully demonstrated how a data-driven approach, combined with appropriate preprocessing and model selection, can significantly enhance customer targeting in banking marketing campaigns.

Model	Dataset	Accuracy	Sensitivity	Specificity	Kappa	Notes
Logistic Regression	SMOTE	86.2%	95.1%	78.6%	0.726	Best balance; high recall
Logistic Regression	Non-SMOTE	90.3%	99.2%	18.7%	0.267	Biased towards majority class
Decision Tree	SMOTE	80.2%	77.5%	85.7%	0.586	Good interpretability
Decision Tree	Non-SMOTE	90.3%	92.7%	60.1%	0.422	Lower ability to detect minority
Random Forest	SMOTE	84.6%	90.3%	77.3%	0.683	Robust but higher complexity
Random Forest	Non-SMOTE	90.4%	92.7%	69.1%	0.422	Overfit risk due to imbalance

CONCLUSION

This project provided a robust predictive framework for identifying customers likely to subscribe to a bank's term deposit product. The integration of SMOTE to manage class imbalance and the application of supervised learning models proved to be a strategic approach. Among the models tested, Logistic Regression on SMOTE-enhanced data emerged as the most accurate and reliable, highlighting the importance of balanced datasets in binary classification tasks.

The findings affirmed that demographic factors (age, job), campaign timing, and call-related metrics (duration, contact method) are crucial in influencing customer behavior. Moreover, past interactions and outcomes were strong predictors of future decisions.

Recommendations

1. **Deploy Predictive Model**: Implement the Logistic Regression model trained on SMOTE data into the bank's customer relationship management (CRM) systems to drive targeted campaigns.

2. **Focus on Key Features**: Prioritize outreach to middle-aged customers, especially those contacted in high-success months (e.g., March, October), and those with a history of successful engagements.

3. **Optimize Call Duration**: Ensure calls are meaningful and exceed the 3-minute threshold when engaging potential customers.

4. **Monitor & Update Model**: Periodically retrain the model with fresh data to maintain prediction accuracy and incorporate new customer behavior trends.

5. **Customer Segmentation**: Leverage the engineered features (e.g., age group, duration group) to create focused customer segments for specialized campaigns.

Implementing these recommendations can lead to higher conversion rates, improved resource allocation, and enhanced customer satisfaction.

How Banks Can Use Predictions:

- **Call Prioritization**: Use model scores to sort call lists by likelihood to convert, ensuring tele-callers focus on high-probability leads.
- **Customized Offers**: Tailor benefits or interest rates for medium-likelihood customers to push them toward conversion.
- **Reduce Call Fatigue**: Avoid contacting low-probability customers too often, improving brand perception

Proposed CRM Integration Workflow:

- **Data Flow**: Integrate the model into the CRM pipeline (e.g., Salesforce, Zoho) via an API or batch prediction system.
- **Input**: Weekly batch of customer data with relevant attributes.
- **Output**: Scores and subscription likelihood flags.
- **Action**: Use flags to auto-tag leads, generate call tasks for telemarketing, or trigger personalized emails/SMS.

REFERENCES

1. Moro, S., Laureano, R., & Cortez, P. (2014). Using Data Mining for Bank Direct Marketing: An Application of the CRISP-DM Methodology. *Expert Systems with Applications*, 39(11), 9290–9296.

2. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, 16, 321–357.

3. R Documentation. (n.d.). https://www.rdocumentation.org

4. Pedregosa, F., et al. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.

5. Bank Marketing Dataset. UCI Machine Learning Repository. https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

6. Kaggle-Data :- https://www.kaggle.com/henriqueyamahata/bank-marketing

7. Guidance provided by Dr. Deepali Malhotra, Delhi School of Management, DTU