IDS 572 - Business Data Mining
Homework 4

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Problem 1:

1. **What is the business problem in this case and how is this business problem converted into an analytics problem?**

Solution:

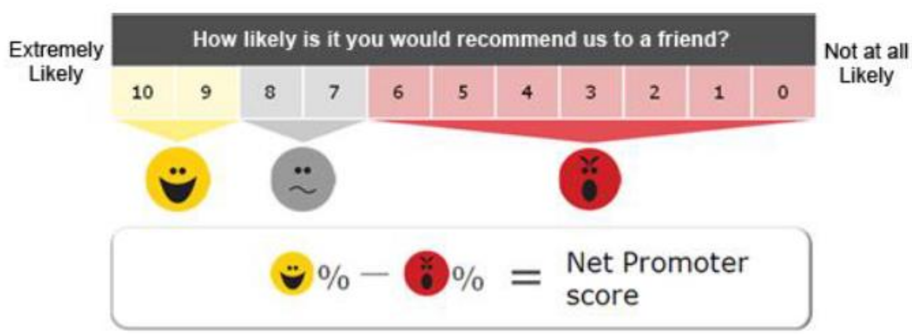
The main problem / objectives of the management at Manipal Health Enterprises is:

- **To enhance customer experience & satisfaction and build customer loyalty through continuous & real time feedback from customers.**

How business problem was converted into Analytics problem:

- Collecting feedback in a structured manner & translate it into meaningful information in real time.
- **Use of Net Promoter Score:** They used the measure called "Net Promoter Score" or NPS. This score is based on a single question: "How likely are you to recommend this product/service to your friend/colleagues". The customers respond on a scale of 0 to 10. Loyal customers are likely to provide a score of 9 or 10, passive customers a score of 7 or 8, while people who score 6 or less are detractors. Subtracting the percentage of detractors from percentage of promoters yield a figure called Net Promoter Score.

NPS question – On a scale of 0 to 10, how likely is it that you would recommend our hospital to a friend or family member?



Source: http://www.netpromotersystem.com/about/measuring-your-net-promoter-score.aspx

- **Patients were asked to give the hospital an overall rating for the services, value for money & accessibility, and the NPS question. Apart from mandatory questions, patients could also provide feedback for specific departments.**
- **The data from this survey could help them deep dive into numerous opportunities like in-depth analysis of department performance, staff or services offered, improving the in-room experience or food & beverages section.**
- **The data from survey could be pivotal as it provides:**
  - **Understanding of the deficiencies in the system and ways of improving them.**
  - **The significant factors influencing the detractors**
  - **The significant factors that improved the Net Promoter Score**
  - **Improvement opportunities within the departments, using NPS**

```r
library(MASS)
library(class)
library(dplyr)

library(ggplot2)
library(randomForest)

library(tidyr)
library(LiblineaR)
library(ROCR)

library(DMwR)

library(caret)
library(tidyverse)

library(readxl)
```

Importing Multi-class Data:

```r
#Importing Multi Class classification data:

MultiTrain <- read_xlsx("MultiTraining.xlsx")
MultiTest <- read_xlsx("MultiTest.xlsx")
```

Pre-processing of Multi-class Data:

```r
#Removing Serial number variable SN and HospitalNo2, as they do not contribute to determi
ning the response variable prediction:
MultiTrain <- MultiTrain %>% select(-SN)
MultiTest <- MultiTest %>% select(-SN)

MultiTrain <- MultiTrain %>% select(-HospitalNo2)
MultiTest <- MultiTest %>% select(-HospitalNo2)

MultiTrain <- MultiTrain %>% select(-AdmissionDate)
MultiTest <- MultiTest %>% select(-AdmissionDate)

MultiTrain <- MultiTrain %>% select(-DischargeDate)
MultiTest <- MultiTest %>% select(-DischargeDate)

#Converting categorical variables into factor

MultiTrain$NPS_Status<- as.factor(MultiTrain$NPS_Status)
MultiTest$NPS_Status<- as.factor(MultiTest$NPS_Status)

MultiTrain$MaritalStatus <- as.factor(MultiTrain$MaritalStatus)
MultiTest$MaritalStatus <- as.factor(MultiTest$MaritalStatus)

MultiTrain$Sex <- as.factor(MultiTrain$Sex)
MultiTest$Sex <- as.factor(MultiTest$Sex)

MultiTrain$BedCategory <- as.factor(MultiTrain$BedCategory)
MultiTest$BedCategory <- as.factor(MultiTest$BedCategory)

MultiTrain$Department <- as.factor(MultiTrain$Department)
MultiTest$Department <- as.factor(MultiTest$Department)
```

```
MultiTrain$InsPayorcategory <- as.factor(MultiTrain$InsPayorcategory)
MultiTest$InsPayorcategory <- as.factor(MultiTest$InsPayorcategory)

MultiTrain$State <- as.factor(MultiTrain$State)
MultiTest$State <- as.factor(MultiTest$State)

MultiTrain$Country <- as.factor(MultiTrain$Country)
MultiTest$Country <- as.factor(MultiTest$Country)

MultiTrain$STATEZONE <- as.factor(MultiTrain$STATEZONE)
MultiTest$STATEZONE <- as.factor(MultiTest$STATEZONE)
```

Importing Binary Data:

```
binaryTrain <- read_xlsx("BinaryTraining.xlsx")
binaryTest <- read_xlsx("BinaryTest.xlsx")
#binaryTrain <- rbind(binaryTrain, binaryTest)
```

Pre-processing of Binary-class Data:

```
#Removing Serial number variable SN and HospitalNo2 from Binary data-set, as they do not contribute to determining the response variable prediction:
binaryTrain <- binaryTrain %>% select(-SN)
binaryTest <- binaryTest %>% select(-SN)

binaryTrain <- binaryTrain %>% select(-HospitalNo2)
binaryTest <- binaryTest %>% select(-HospitalNo2)

binaryTrain <- binaryTrain %>% select(-AdmissionDate)
binaryTest <- binaryTest %>% select(-AdmissionDate)

binaryTrain <- binaryTrain %>% select(-DischargeDate)
binaryTest <- binaryTest %>% select(-DischargeDate)

#Converting categorical variables into factor

binaryTrain$NPS_Status<- as.factor(binaryTrain$NPS_Status)
binaryTest$NPS_Status<- as.factor(binaryTest$NPS_Status)

binaryTrain$MaritalStatus <- as.factor(binaryTrain$MaritalStatus)
binaryTest$MaritalStatus <- as.factor(binaryTest$MaritalStatus)

binaryTrain$Sex <- as.factor(binaryTrain$Sex)
binaryTest$Sex <- as.factor(binaryTest$Sex)

binaryTrain$BedCategory <- as.factor(binaryTrain$BedCategory)
binaryTest$BedCategory <- as.factor(binaryTest$BedCategory)

binaryTrain$Department <- as.factor(binaryTrain$Department)
binaryTest$Department <- as.factor(binaryTest$Department)

binaryTrain$InsPayorcategory <- as.factor(binaryTrain$InsPayorcategory)
binaryTest$InsPayorcategory <- as.factor(binaryTest$InsPayorcategory)

binaryTrain$State <- as.factor(binaryTrain$State)
binaryTest$State <- as.factor(binaryTest$State)
```

```
binaryTrain$Country <- as.factor(binaryTrain$Country)
binaryTest$Country <- as.factor(binaryTest$Country)

binaryTrain$STATEZONE <- as.factor(binaryTrain$STATEZONE)
binaryTest$STATEZONE <- as.factor(binaryTest$STATEZONE)
```

4. What is quasi-complete separation? Which variables in the Manipal Hospital dataset are leading to quasi-complete separation?

Quasi complete separation in logistic regression happens when the target variables separates a predictor variable or a set of predictor variables almost completely. For example:

Gender	Marital Status	Target
Male	Married	Yes
Male	Single	Yes
Female	Single	No
Male	Single	Yes
Male	Married	Yes
Male	Married	Yes
Female	Single	No

In this example, the variable **Marital Status is causing Quasi Complete Separation** as, the class Married is predicting the Target class completely as Yes. For class Single, The Target takes both Yes and No values.

The variable **Gender is causing Complete separation** in this example, because for all instances of Male, the Target class is Yes and for all Female instances the target class is No.

Quasi-Complete Separation in Manipal Health Enterprises Data:

```
table(MultiTrain$MaritalStatus,MultiTrain$NPS_Status) %>%
  set_caption("MaritalStatus and NPS Status.")

table(MultiTrain$Sex,MultiTrain$NPS_Status)%>%
  set_caption("Sex and NPS Status.")

table(MultiTrain$BedCategory,MultiTrain$NPS_Status)%>%
  set_caption("BedCategory and NPS Status.")

table(MultiTrain$Department,MultiTrain$NPS_Status)%>%
  set_caption("Department and NPS Status.")

table(MultiTrain$InsPayorcategory,MultiTrain$NPS_Status)%>%
  set_caption("InsPayorcategory and NPS Status.")

table(MultiTrain$State,MultiTrain$NPS_Status)%>%
  set_caption("State and NPS Status.")

table(MultiTrain$Country,MultiTrain$NPS_Status)%>%
  set_caption("Country and NPS Status.")

table(MultiTrain$STATEZONE,MultiTrain$NPS_Status)%>%
  set_caption("STATEZONE and NPS Status.")

table(MultiTrain$EM_IMMEDIATEATTENTION,MultiTrain$NPS_Status)%>%
  set_caption("EM_IMMEDIATEATTENTION and NPS Status.")
```

```
table(MultiTrain$EM_NURSING,MultiTrain$NPS_Status)%>%
  set_caption("EM_NURSING and NPS Status.")

table(MultiTrain$EM_DOCTOR,MultiTrain$NPS_Status)%>%
  set_caption("EM_DOCTOR and NPS Status.")

table(MultiTrain$EM_OVERALL,MultiTrain$NPS_Status)%>%
  set_caption("EM_OVERALL and NPS Status.")

table(MultiTrain$DOC_TREATMENTEXPLAINATION,MultiTrain$NPS_Status)%>%
  set_caption("DOC_TREATMENTEXPLAINATION and NPS Status.")

table(MultiTrain$DOC_ATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("DOC_ATTITUDE and NPS Status.")

table(MultiTrain$DOC_VISITS,MultiTrain$NPS_Status)%>%
  set_caption("DOC_VISITS and NPS Status.")

table(MultiTrain$DOC_TREATMENTEFFECTIVENESS,MultiTrain$NPS_Status)%>%
  set_caption("DOC_TREATMENTEFFECTIVENESS and NPS Status.")

table(MultiTrain$CE_ACCESSIBILITY,MultiTrain$NPS_Status)%>%
  set_caption("CE_ACCESSIBILITY and NPS Status.")

table(MultiTrain$CE_CSAT,MultiTrain$NPS_Status)%>%
  set_caption("CE_CSAT and NPS Status.")

table(MultiTrain$CE_VALUEFORMONEY,MultiTrain$NPS_Status)%>%
  set_caption("CE_VALUEFORMONEY and NPS Status.")

table(MultiTrain$CE_NPS,MultiTrain$NPS_Status)%>%
  set_caption("CE_NPS and NPS Status.")

table(MultiTrain$AD_TIME,MultiTrain$NPS_Status)%>%
  set_caption("AD_TIME and NPS Status.")

table(MultiTrain$AD_TARRIFFPACKAGESEXPLAINATION,MultiTrain$NPS_Status)%>%
  set_caption("AD_TARRIFFPACKAGESEXPLAINATION and NPS Status.")

table(MultiTrain$AD_STAFFATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("AD_STAFFATTITUDE and NPS Status.")

table(MultiTrain$INR_ROOMCLEANLINESS,MultiTrain$NPS_Status)%>%
  set_caption("INR_ROOMCLEANLINESS and NPS Status.")

table(MultiTrain$INR_ROOMPEACE,MultiTrain$NPS_Status)%>%
  set_caption("INR_ROOMPEACE and NPS Status.")

table(MultiTrain$INR_ROOMEQUIPMENT,MultiTrain$NPS_Status)%>%
  set_caption("INR_ROOMEQUIPMENT and NPS Status.")

table(MultiTrain$INR_ROOMAMBIENCE,MultiTrain$NPS_Status)%>%
  set_caption("INR_ROOMAMBIENCE and NPS Status.")

table(MultiTrain$FNB_FOODQUALITY,MultiTrain$NPS_Status)%>%
  set_caption("FNB_FOODQUALITY and NPS Status.")

table(MultiTrain$FNB_FOODDELIVERYTIME,MultiTrain$NPS_Status)%>%
  set_caption("FNB_FOODDELIVERYTIME and NPS Status.")
```

```r
table(MultiTrain$FNB_DIETICIAN,MultiTrain$NPS_Status)%>%
  set_caption("FNB_DIETICIAN and NPS Status.")

table(MultiTrain$FNB_STAFFATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("FNB_STAFFATTITUDE and NPS Status.")

table(MultiTrain$AE_ATTENDEECARE,MultiTrain$NPS_Status)%>%
  set_caption("AE_ATTENDEECARE and NPS Status.")

table(MultiTrain$AE_PATIENTSTATUSINFO,MultiTrain$NPS_Status)%>%
  set_caption("AE_PATIENTSTATUSINFO and NPS Status.")

table(MultiTrain$AE_ATTENDEEFOOD,MultiTrain$NPS_Status)%>%
  set_caption("AE_ATTENDEEFOOD and NPS Status.")

table(MultiTrain$NS_CALLBELLRESPONSE,MultiTrain$NPS_Status)%>%
  set_caption("NS_CALLBELLRESPONSE and NPS Status.")

table(MultiTrain$NS_NURSESATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("NS_NURSESATTITUDE and NPS Status.")

table(MultiTrain$NS_NURSEPROACTIVENESS,MultiTrain$NPS_Status)%>%
  set_caption("NS_NURSEPROACTIVENESS and NPS Status.")

table(MultiTrain$NS_NURSEPATIENCE,MultiTrain$NPS_Status)%>%
  set_caption("NS_NURSEPATIENCE and NPS Status.")

table(MultiTrain$OVS_OVERALLSTAFFATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("OVS_OVERALLSTAFFATTITUDE and NPS Status.")

table(MultiTrain$OVS_OVERALLSTAFFPROMPTNESS,MultiTrain$NPS_Status)%>%
  set_caption("OVS_OVERALLSTAFFPROMPTNESS and NPS Status.")

table(MultiTrain$OVS_SECURITYATTITUDE,MultiTrain$NPS_Status)%>%
  set_caption("OVS_SECURITYATTITUDE and NPS Status.")

table(MultiTrain$DP_DISCHARGETIME,MultiTrain$NPS_Status)%>%
  set_caption("DP_DISCHARGETIME and NPS Status.")

table(MultiTrain$DP_DISCHARGEQUERIES,MultiTrain$NPS_Status)%>%
  set_caption("DP_DISCHARGEQUERIES and NPS Status.")

table(MultiTrain$DP_DISCHARGEPROCESS,MultiTrain$NPS_Status)%>%
  set_caption("DP_DISCHARGEPROCESS and NPS Status.")
```

MaritalStatus and NPS Status.

	Detractor	Passive	Promotor
Divorced	1	0	0
Married	326	869	2196
Separated	0	0	1
Single	175	476	941
Widowed	0	2	2

Sex and NPS Status.

	Detractor	Passive	Promotor
F	198	620	1349
M	304	727	1791

BedCategory and NPS Status.

	Detractor	Passive	Promotor
CCU	0	0	1
DAYCARE	6	22	63
GENERAL	107	280	963
GENERAL HD	6	25	64
ITU	0	0	1
Renal ICU	0	0	2
SEMISPECIAL	231	614	1221
SEMISPECIAL HD	5	4	20
SPECIAL	111	319	594
ULTRA DLX	4	17	35
ULTRA SPL	32	66	176

Department and NPS Status.

	Detractor	Passive	Promotor
CARDIOLOGY	34	79	276
GEN	264	599	1376
GYNAEC	30	104	195
ORTHO	32	100	256
PEDIATRIC	64	211	348
RENAL	12	48	147
SPECIAL	66	206	542

InsPayorcategory and NPS Status.

	Detractor	Passive	Promotor
CORPORATE	30	86	267
EXEMPTION	31	126	387
INSURANCE	222	588	1027
INTERNATIONAL	6	15	59
PATIENT	213	532	1400

State and NPS Status.

	Detractor	Passive	Promotor
Africa	0	0	3
Andaman And Nicobar	0	0	2
Andhra Pradesh	23	39	117
Assam	1	4	14
Bangladesh	0	0	6
Bhubaneshwar	0	0	1
Bihar	1	5	7
Chandigarh	0	0	1
Chhattisgarh	2	0	1
Darjeeling	0	0	1
Delhi	1	1	3
Doha	0	0	1
Germany	0	0	1
Goa	1	2	12
Gujarat	0	0	3
Haryana	0	2	2
International	0	0	6
Iraq	0	1	7
Jharkand	0	0	1
Jharkhand	1	5	10
Karnataka	415	1134	2401
Kenya	0	0	1
Kerala	7	14	37
Kolkata	0	3	1
Kolkatta	1	0	0
Madhya Pradesh	1	1	5
Maharashtra	1	3	11
Maldives	2	2	6
Manipur	0	1	7
Mauritius	0	2	3
Meghalaya	0	0	3
Mizoram	0	0	2
Mongolia	1	0	0
Mumbai	0	0	1
Muscat	0	0	1
Nepal	0	1	0

New Zealand	1	0	0
Nigeria	0	0	7
Oman	0	4	3
Ontario	1	0	0
Orissa	3	7	14
Rajasthan	0	1	7
Ranchi	1	0	0
RWANDA	1	0	4
Saudi Arabia	0	0	2
Sikkim	0	0	1
Tamil Nadu	9	27	89
Tanzania	0	3	24
Tripura	0	1	3
UAE	0	0	2
UK	1	0	0
Unknown	4	23	45
USA	0	0	1
Uttar Pradesh	1	5	8
Uttarakhand	0	1	4
West Bengal	22	54	248
Zimbabwe	0	1	0

Country and NPS Status.

	Detractor	Passive	Promotor
Africa	1	0	4
ANGOLA	0	1	0
BANGLADESH	0	0	7
CANADA	1	0	0
FIJI	0	0	1
GERMANY	0	0	1
INDIA	495	1330	3055
IRAQ	0	1	9
ISLAMIC REPUBLIC OF IRAN	0	0	1
KENYA	0	0	1
MALDIVES	2	2	6
MAURITIUS	0	2	5
MONGOLIA	1	0	0
MOZAMBIQUE	0	0	1
NEPAL	0	1	1
NEW ZEALAND	1	0	0
NIGERIA	0	0	9
OMAN	0	4	5
QATAR	0	0	1
Saudi Arabia	0	0	1
SAUDI ARABIA	0	0	1
SUDAN	0	1	0
UGANDA	0	0	2
UNITED ARAB EMIRATES	0	0	2
UNITED KINGDOM	1	0	0
UNITED REPUBLIC OF TANZANIA	0	3	24
UNITED STATES OF AMERICA	0	0	1
YEMEN	0	1	2
ZIMBABWE	0	1	0

STATEZONE and NPS Status.

	Detractor	Passive	Promotor
CENTRAL	3	1	6
EAST	30	80	315
INTERNATIONAL	7	14	78
NORTH	2	9	18
SOUTH	454	1214	2644
Unknown	4	23	45
WEST	2	6	34

EM_IMMEDIATEATTENTION and NPS Status.

	Detractor	Passive	Promotor
1	10	7	3
2	30	25	15
3	151	223	272
4	311	1092	2850

EM_NURSING and NPS Status.

	Detractor	Passive	Promotor
1	8	1	3
2	24	17	10
3	147	210	220
4	323	1119	2907

EM_DOCTOR and NPS Status.

	Detractor	Passive	Promotor
1	7	4	0
2	20	18	11
3	133	170	185
4	342	1155	2944

EM_OVERALL and NPS Status.

	Detractor	Passive	Promotor
1	11	2	2
2	28	23	9
3	180	263	283
4	283	1059	2846

DOC_TREATMENTEXPLAINATION and NPS Status.

	Detractor	Passive	Promotor
1	10	2	0
2	36	21	14
3	189	359	605
4	267	965	2521

DOC_ATTITUDE and NPS Status.

	Detractor	Passive	Promotor
1	8	2	2
2	34	21	8
3	178	365	610
4	282	959	2520

DOC_VISITS and NPS Status.

	Detractor	Passive	Promotor
1	18	4	1
2	49	43	19
3	233	460	670
4	202	840	2450

DOC_TREATMENTEFFECTIVENESS and NPS Status.

	Detractor	Passive	Promotor
1	8	0	0
2	35	22	8
3	209	413	622
4	250	912	2510

CE_ACCESSIBILITY and NPS Status.

	Detractor	Passive	Promotor
1	12	1	2
2	96	39	25
3	245	541	727
4	149	766	2386

CE_CSAT and NPS Status.

	Detractor	Passive	Promotor
1	23	0	2
2	109	25	7
3	293	869	983
4	77	453	2148

CE_VALUEFORMONEY and NPS Status.

	Detractor	Passive	Promotor
1	45	3	7
2	185	122	53
3	223	875	1293
4	49	347	1787

CE_NPS and NPS Status.

	Detractor	Passive	Promotor
0	26	0	0
1	20	0	0
2	28	0	0
3	21	0	0
4	41	0	0
5	161	0	0
6	205	0	0
7	0	387	0
8	0	960	0
9	0	0	1650
10	0	0	1490

AD_TIME and NPS Status.

	Detractor	Passive	Promotor
1	25	39	34
2	48	109	123
3	315	723	1137
4	114	476	1846

AD_TARRIFFPACKAGESEXPLAINATION and NPS Status.

	Detractor	Passive	Promotor
1	32	25	12
2	69	134	96
3	331	785	1272
4	70	403	1760

AD_STAFFATTITUDE and NPS Status.

	Detractor	Passive	Promotor
1	19	9	7
2	41	57	66
3	289	603	969
4	153	678	2098

INR_ROOMCLEANLINESS and NPS Status.

	Detractor	Passive	Promotor
1	26	19	18
2	79	92	99
3	283	635	1152
4	114	601	1871

INR_ROOMPEACE and NPS Status.

	Detractor	Passive	Promotor
1	37	26	23
2	55	120	110
3	313	697	1157
4	97	504	1850

INR_ROOMEQUIPMENT and NPS Status.

	Detractor	Passive	Promotor
1	22	3	7
2	58	79	68
3	304	698	1099
4	118	567	1966

INR_ROOMAMBIENCE and NPS Status.

	Detractor	Passive	Promotor
1	23	12	9
2	83	106	57
3	307	736	1221
4	89	493	1853

FNB_FOODQUALITY and NPS Status.

	Detractor	Passive	Promotor
1	58	88	70
2	108	239	311
3	312	835	1667
4	24	185	1092

FNB_FOODDELIVERYTIME and NPS Status.

	Detractor	Passive	Promotor
1	48	40	31
2	66	141	141
3	336	843	1408
4	52	323	1560

FNB_DIETICIAN and NPS Status.

	Detractor	Passive	Promotor
1	28	29	25
2	63	137	122
3	354	810	1397
4	57	371	1596

FNB_STAFFATTITUDE and NPS Status.

	Detractor	Passive	Promotor
1	12	10	8
2	46	58	51
3	319	691	1160
4	125	588	1921

AE_ATTENDEECARE and NPS Status.

	Detractor	Passive	Promotor
1	24	10	7
2	47	65	35
3	312	681	1125
4	119	591	1973

AE_PATIENTSTATUSINFO and NPS Status.

	Detractor	Passive	Promotor
1	19	6	0
2	54	49	19
3	304	716	1102
4	125	576	2019

AE_ATTENDEEFOOD and NPS Status.

	Detractor	Passive	Promotor
1	49	74	57
2	95	194	168
3	317	793	1421
4	41	286	1494

NS_CALLBELLRESPONSE and NPS Status.

	Detractor	Passive	Promotor
1	18	14	2
2	30	44	40
3	170	402	719
4	284	887	2379

NS_NURSESATTITUDE and NPS Status.

	Detractor	Passive	Promotor
1	7	1	0
2	28	18	13
3	135	357	645
4	332	971	2482

NS_NURSEPROACTIVENESS and NPS Status.

	Detractor	Passive	Promotor
2	52	56	14
3	200	444	764
4	250	847	2362

```
NS_NURSEPATIENCE and NPS Status.
   Detractor Passive Promotor
 1        10       3        0
 2        34      41       13
 3       196     436      729
 4       262     867     2398

OVS_OVERALLSTAFFATTITUDE and NPS Status.
   Detractor Passive Promotor
 1         7       1        0
 2        27       9        5
 3       209     451      715
 4       259     886     2420

OVS_OVERALLSTAFFPROMPTNESS and NPS Status.
   Detractor Passive Promotor
 1        17       5        3
 2        48      45       15
 3       233     503      760
 4       204     794     2362

OVS_SECURITYATTITUDE and NPS Status.
   Detractor Passive Promotor
 1         9       6        4
 2        32      44       40
 3       219     496      805
 4       242     801     2291

DP_DISCHARGETIME and NPS Status.
   Detractor Passive Promotor
 1        50      63       41
 2        92     130      122
 3       318     790     1333
 4        42     364     1644

DP_DISCHARGEQUERIES and NPS Status.
   Detractor Passive Promotor
 1        27      22       10
 2        58      76       52
 3       336     671     1029
 4        81     578     2049

DP_DISCHARGEPROCESS and NPS Status.
   Detractor Passive Promotor
 1        37      34       21
 2        70     111       87
 3       333     753     1173
 4        62     449     1859
```

From the tables above, we see that for some variables, certain classes can predict the target class definitievely, thus they are causing Quasi Complete Separartion

By looking at the tables obtained from table function, we find that variables causing quasi complete separation are:
MaritalStatus
BedCategory
Statte
Country
EM_Doctor
Doc_TreatmentExplanation
CE_CSAT
CE_NPS
AE_PatientStatusInfo
NS_NursePatience
OVS_OverallStaffAttitude

```r
library(brglm2)
library(brglm)

binaryTrain$NPS_Status<- as.factor(binaryTrain$NPS_Status)

glm(NPS_Status ~ .-CE_NPS, data = binaryTrain, family='binomial',
    method = "detect_separation", linear_program = "dual")

## Separation: FALSE
## Existence of maximum likelihood estimates
##                        (Intercept)                                  SN
##                                Inf                                   0
##                        HospitalNo2                 MaritalStatusMarried
##                                  0                                 Inf
##             MaritalStatusSeparated                 MaritalStatusSingle
##                                Inf                                 Inf
##               MaritalStatusWidowed                              AgeYrs
##                                Inf                                   0
##                               SexM                 BedCategoryDAYCARE
##                                  0                                -Inf
##                 BedCategoryGENERAL               BedCategoryGENERAL HD
##                               -Inf                                -Inf
##                     BedCategoryITU                BedCategoryRenal ICU
##                                Inf                                 Inf
##             BedCategorySEMISPECIAL           BedCategorySEMISPECIAL HD
##                               -Inf                                -Inf
##                 BedCategorySPECIAL                BedCategoryULTRA DLX
##                               -Inf                                -Inf
##               BedCategoryULTRA SPL                       DepartmentGEN
##                               -Inf                                   0
##                   DepartmentGYNAEC                    DepartmentORTHO
##                                  0                                   0
##               DepartmentPEDIATRIC                    DepartmentRENAL
##                                  0                                   0
##                 DepartmentSPECIAL                       Estimatedcost
##                                  0                                   0
##         InsPayorcategoryEXEMPTION           InsPayorcategoryINSURANCE
##                                  0                                   0
##     InsPayorcategoryINTERNATIONAL             InsPayorcategoryPATIENT
##                                  0                                   0
##          StateAndaman And Nicobar                StateAndhra Pradesh
##                                Inf                                -Inf
##                        StateAssam                     StateBangladesh
##                               -Inf                                 Inf
##                  StateBhubaneshwar                         StateBihar
##                                Inf                                -Inf
##                   StateChandigarh                  StateChhattisgarh
##                                Inf                                -Inf
##                   StateDarjeeling                         StateDelhi
##                                Inf                                -Inf
##                          StateDoha                       StateGermany
##                                Inf                                 Inf
##                           StateGoa                       StateGujarat
##                               -Inf                                 Inf
##                       StateHaryana                 StateInternational
##                               -Inf                                 Inf
```

```
##                           StateIraq                        StateJharkand 
##                                -Inf                                  Inf 
##                      StateJharkhand                       StateKarnataka 
##                                -Inf                                 -Inf 
##                          StateKenya                          StateKerala 
##                                 Inf                                 -Inf 
##                        StateKolkata                        StateKolkatta 
##                                -Inf                                 -Inf 
##                 StateMadhya Pradesh                     StateMaharashtra 
##                                -Inf                                 -Inf 
##                      StateMaldives                         StateManipur 
##                                -Inf                                 -Inf 
##                     StateMauritius                       StateMeghalaya 
##                                -Inf                                  Inf 
##                        StateMizoram                        StateMongolia 
##                                 Inf                                 -Inf 
##                         StateMumbai                          StateMuscat 
##                                 Inf                                  Inf 
##                          StateNepal                     StateNew Zealand 
##                                -Inf                                 -Inf 
##                        StateNigeria                            StateOman 
##                                 Inf                                 -Inf 
##                        StateOntario                          StateOrissa 
##                                -Inf                                 -Inf 
##                     StateRajasthan                          StateRanchi 
##                                -Inf                                 -Inf 
##                         StateRWANDA                    StateSaudi Arabia 
##                                   0                                  Inf 
##                         StateSikkim                      StateTamil Nadu 
##                                 Inf                                 -Inf 
##                      StateTanzania                         StateTripura 
##                                -Inf                                 -Inf 
##                            StateUAE                              StateUK 
##                                 Inf                                 -Inf 
##                        StateUnknown                             StateUSA 
##                                -Inf                                  Inf 
##                  StateUttar Pradesh                     StateUttarakhand 
##                                -Inf                                 -Inf 
##                    StateWest Bengal                        StateZimbabwe 
##                                -Inf                                 -Inf 
##                      CountryANGOLA                    CountryBANGLADESH 
##                                -Inf                                  Inf 
##                      CountryCANADA                          CountryFIJI 
##                                  NA                                  Inf 
##                     CountryGERMANY                         CountryINDIA 
##                                  NA                                    0 
##                         CountryIRAQ    CountryISLAMIC REPUBLIC OF IRAN 
##                                   0                                  Inf 
##                        CountryKENYA                      CountryMALDIVES 
##                                  NA                                   NA 
##                    CountryMAURITIUS                      CountryMONGOLIA 
##                                   0                                   NA 
##                   CountryMOZAMBIQUE                         CountryNEPAL 
##                                 Inf                                    0 
##                  CountryNEW ZEALAND                       CountryNIGERIA 
```

```
##                                   NA                                  Inf
##                          CountryOMAN                         CountryQATAR
##                                    0                                   NA
##                   CountrySaudi Arabia                  CountrySAUDI ARABIA
##                                  Inf                                   NA
##                         CountrySUDAN                        CountryUGANDA
##                                 -Inf                                   NA
##         CountryUNITED ARAB EMIRATES              CountryUNITED KINGDOM
##                                   NA                                   NA
## CountryUNITED REPUBLIC OF TANZANIA    CountryUNITED STATES OF AMERICA
##                                   NA                                   NA
##                         CountryYEMEN                      CountryZIMBABWE
##                                   NA                                   NA
##                        STATEZONEEAST               STATEZONEINTERNATIONAL
##                                   NA                                   NA
##                       STATEZONENORTH                       STATEZONESOUTH
##                                   NA                                   NA
##                     STATEZONEUnknown                        STATEZONEWEST
##                                   NA                                   NA
##                     CE_ACCESSIBILITY                              CE_CSAT
##                                    0                                    0
##                     CE_VALUEFORMONEY                EM_IMMEDIATEATTENTION
##                                    0                                    0
##                           EM_NURSING                            EM_DOCTOR
##                                    0                                    0
##                           EM_OVERALL                              AD_TIME
##                                    0                                    0
##      AD_TARRIFFPACKAGESEXPLAINATION                    AD_STAFFATTITUDE
##                                    0                                    0
##                  INR_ROOMCLEANLINESS                         INR_ROOMPEACE
##                                    0                                    0
##                    INR_ROOMEQUIPMENT                     INR_ROOMAMBIENCE
##                                    0                                    0
##                      FNB_FOODQUALITY                 FNB_FOODDELIVERYTIME
##                                    0                                    0
##                        FNB_DIETICIAN                    FNB_STAFFATTITUDE
##                                    0                                    0
##                      AE_ATTENDEECARE                 AE_PATIENTSTATUSINFO
##                                    0                                    0
##                      AE_ATTENDEEFOOD            DOC_TREATMENTEXPLAINATION
##                                    0                                    0
##                         DOC_ATTITUDE                           DOC_VISITS
##                                    0                                    0
##          DOC_TREATMENTEFFECTIVENESS                  NS_CALLBELLRESPONSE
##                                    0                                    0
##                    NS_NURSESATTITUDE               NS_NURSEPROACTIVENESS
##                                    0                                    0
##                     NS_NURSEPATIENCE             OVS_OVERALLSTAFFATTITUDE
##                                    0                                    0
##          OVS_OVERALLSTAFFPROMPTNESS                OVS_SECURITYATTITUDE
##                                    0                                    0
##                     DP_DISCHARGETIME                  DP_DISCHARGEQUERIES
##                                    0                                    0
##                  DP_DISCHARGEPROCESS                        AdmissionDate
##                                    0                                    0
```

```
##                        DischargeDate                              LengthofStay
##                                    0                                        NA
## 0: finite value, Inf: infinity, -Inf: -infinity
```

On running glm, with argument Method-separation, we also get variables MaritalStatus, BedCategory, State & Country as causing Quasi complete separation.

5. What is orthogonal polynomial coding and how is it implemented in contrasting ordinal variables?

Orthogonal polynomial coding is a form of trend analysis in that it is looking for the linear, quadratic and cubic trends in the categorical variable. This type of coding tries to find out the impact of variable transformations on the target variable. The transformations include Linear, Quadratic & Cubic transformation of predictor.

This coding system should be used only with an ordinal variable in which the levels are equally spaced. Examples of such a variable might be survey questions like satisfaction scale (Extremely Unhappy, Okay , Extremely happy) or clothes Size chart (XS,S,M,L,XL).

The table below shows the contrast coefficients for the linear, quadratic and cubic trends for the four levels. In R it is not necessary to compute these values since this contrast can be obtained for any categorical variable by using the contr.poly function. This is also the default contrast used for ordered factor variables.

Implementation of Orthogonal Polynomial Coding in factor variables in the Manipal Health Data: (Variables used - CE_Accessibility, CE_CSAT)

```
orth.poly <- binaryTrain

contr.poly(4)

##              .L   .Q         .C
## [1,] -0.6708204  0.5 -0.2236068
## [2,] -0.2236068 -0.5  0.6708204
## [3,]  0.2236068 -0.5 -0.6708204
## [4,]  0.6708204  0.5  0.2236068

orth.poly$Ord.ACCESSIBILITY<- factor(orth.poly$CE_ACCESSIBILITY, order = TRUE, levels = c
("1", "2", "3", "4"))

contrasts(orth.poly$Ord.ACCESSIBILITY) = contr.poly(4)
summary(glm(NPS_Status ~ Ord.ACCESSIBILITY, orth.poly, family = "binomial"))

##
## Call:
## glm(formula = NPS_Status ~ Ord.ACCESSIBILITY, family = "binomial",
##     data = orth.poly)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6019  -1.1445   0.8057   0.8057   2.0074
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -0.6694     0.1982  -3.378 0.000731 ***
## Ord.ACCESSIBILITY.L   2.2582     0.5126   4.405 1.06e-05 ***
## Ord.ACCESSIBILITY.Q   0.4255     0.3964   1.074 0.283027
```

```
## Ord.ACCESSIBILITY.C  -0.4461     0.2268  -1.967 0.049228 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6578.3  on 4988  degrees of freedom
## Residual deviance: 6142.6  on 4985  degrees of freedom
## AIC: 6150.6
##
## Number of Fisher Scoring iterations: 4
```

For variable CE_ACCESSIBILITY, the linear and cubic coefficients have P-values less than 0.05 and thus are significant in determining the target variable NPS_Status. But the Quadratic coefficient has a larger p-value and thus is not significant.

```
orth.poly$Ord.CSAT <- factor(orth.poly$CE_CSAT, order = TRUE, levels = c("1", "2", "3", "
4"))

contrasts(orth.poly$Ord.CSAT) = contr.poly(4)
summary(glm(NPS_Status ~ Ord.CSAT, orth.poly, family = "binomial"))

##
## Call:
## glm(formula = NPS_Status ~ Ord.CSAT, family = "binomial", data = orth.poly)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8000  -1.1073   0.6641   0.6641   2.4506
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.0405     0.2089  -4.982 6.30e-07 ***
## Ord.CSAT.L    3.1998     0.5032   6.359 2.04e-10 ***
## Ord.CSAT.Q    1.0381     0.4177   2.485  0.01295 *
## Ord.CSAT.C   -1.0089     0.3095  -3.260  0.00111 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6578.3  on 4988  degrees of freedom
## Residual deviance: 5692.8  on 4985  degrees of freedom
## AIC: 5700.8
##
## Number of Fisher Scoring iterations: 5

LRTrain <- MultiTrain
LRTest <- MultiTest
```

For variable CE_CSAT, the linear, quadratic and cubic coefficients have P-values less than 0.05 and thus are significant in determining the target variable NPS_Status.

6.

Convert multi-class problem to binary class problem:

```
# Converting multi class to binary class problem: by converting individual classes of tar
get variable into variables Detractors, Passive & Promoters

LRTrain <- LRTrain %>%
  mutate(Detractors = ifelse(NPS_Status == "Detractor", "Yes", "No") )

LRTrain <- LRTrain %>% select(-NPS_Status)

LRTest <- LRTest %>%
  mutate(Detractors = ifelse(NPS_Status == "Detractor", "Yes", "No") )

LRTest <- LRTest %>% select(-NPS_Status)

LRTrain$Detractors <- as.factor(LRTrain$Detractors)
LRTest$Detractors <- as.factor(LRTest$Detractors)
```

Removing variables that cause Quasi-complete Separation:

```
#Removing variables found out in Quasi Complete separation from Train & Test: MaritalStat
us,BedCategory,State, Country, CE_NPS

remove.vars <- names(LRTrain) %in% c("MaritalStatus", "BedCategory", "State", "Country",
"CE_NPS")
LRTrain <- LRTrain[!remove.vars]
LRTest <- LRTest[!remove.vars]
```

Convert survey questionnaire responses to Ordinal:

```
#Converting survey responses into ordinal variables by normalizing
options(digits=2)
normalize <- function(x) {
    return ((x - min(x)) / (max(x) - min(x)))
}

LRordinalTr <- as.data.frame(lapply(LRTrain[7:35], normalize))
LRTrain[7:35] <- LRordinalTr[1:29]

LRordinalTst <- as.data.frame(lapply(LRTest[7:35], normalize))
LRTest[7:35] <- LRordinalTst[1:29]
```

Step-wise Logistic Regression for Binary Class problem:

```
# Logistic Regression on binary classification

FullGlmModel <- glm(Detractors ~. , data = LRTrain, family = "binomial")

StepGlmModel <- glm(Detractors ~. , data = LRTrain, family = "binomial")%>%
  stepAIC(trace = FALSE)

summary(FullGlmModel)

##
## Call:
## glm(formula = Detractors ~ ., family = "binomial", data = LRTrain)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.102  -0.406  -0.209  -0.122   3.421
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    6.46e+00   1.13e+00    5.72  1.0e-08 ***
## AgeYrs                         4.87e-03   3.34e-03    1.46  0.14471
## SexM                           1.92e-01   1.21e-01    1.59  0.11253
## DepartmentGEN                  9.07e-02   2.55e-01    0.36  0.72251
## DepartmentGYNAEC               4.94e-02   3.37e-01    0.15  0.88356
## DepartmentORTHO               -2.72e-01   3.26e-01   -0.83  0.40520
## DepartmentPEDIATRIC            1.20e-01   3.32e-01    0.36  0.71840
## DepartmentRENAL               -7.76e-01   4.18e-01   -1.85  0.06372 .
## DepartmentSPECIAL             -2.95e-01   2.81e-01   -1.05  0.29268
## Estimatedcost                  1.66e-07   7.71e-07    0.21  0.82998
## InsPayorcategoryEXEMPTION     -2.63e-01   3.28e-01   -0.80  0.42369
## InsPayorcategoryINSURANCE      1.74e-02   2.43e-01    0.07  0.94303
## InsPayorcategoryINTERNATIONAL  1.91e-01   8.15e-01    0.23  0.81470
## InsPayorcategoryPATIENT        1.94e-01   2.42e-01    0.80  0.42113
## STATEZONEEAST                 -1.49e+00   9.75e-01   -1.53  0.12636
## STATEZONEINTERNATIONAL        -1.25e+00   1.22e+00   -1.03  0.30331
## STATEZONENORTH                -1.07e+00   1.24e+00   -0.86  0.38791
## STATEZONESOUTH                -1.04e+00   9.51e-01   -1.09  0.27554
## STATEZONEUnknown              -1.53e+00   1.10e+00   -1.39  0.16482
## STATEZONEWEST                 -1.13e+00   1.24e+00   -0.91  0.36381
## CE_ACCESSIBILITY              -2.34e+00   3.04e-01   -7.70  1.3e-14 ***
## CE_VALUEFORMONEY              -3.83e+00   3.11e-01  -12.32  < 2e-16 ***
## EM_IMMEDIATEATTENTION         -2.63e-01   4.55e-01   -0.58  0.56427
## EM_NURSING                    -9.06e-01   5.24e-01   -1.73  0.08371 .
## EM_OVERALL                    -2.97e-01   5.40e-01   -0.55  0.58241
## AD_TIME                        7.22e-01   3.30e-01    2.19  0.02879 *
## AD_TARRIFFPACKAGESEXPLAINATION -9.80e-01   3.56e-01   -2.76  0.00586 **
## AD_STAFFATTITUDE              -2.05e-01   3.82e-01   -0.54  0.59248
## INR_ROOMCLEANLINESS           -5.43e-01   3.56e-01   -1.52  0.12774
## INR_ROOMPEACE                 -1.28e-01   3.32e-01   -0.39  0.69916
## INR_ROOMEQUIPMENT              3.20e-01   3.96e-01    0.81  0.41951
## INR_ROOMAMBIENCE              -2.66e-01   4.44e-01   -0.60  0.54875
```

```
## FNB_FOODQUALITY                -3.26e-01   3.24e-01   -1.01  0.31315
## FNB_FOODDELIVERYTIME           -7.17e-01   3.54e-01   -2.03  0.04248 *
## FNB_DIETICIAN                  -3.83e-02   3.81e-01   -0.10  0.91978
## FNB_STAFFATTITUDE               1.85e-01   4.03e-01    0.46  0.64568
## AE_ATTENDEECARE                -4.03e-01   3.75e-01   -1.08  0.28195
## AE_ATTENDEEFOOD                 2.64e-01   3.39e-01    0.78  0.43699
## DOC_TREATMENTEXPLAINATION      -4.59e-01   5.43e-01   -0.85  0.39736
## DOC_ATTITUDE                    3.44e-01   5.73e-01    0.60  0.54845
## DOC_VISITS                     -1.16e+00   4.16e-01   -2.78  0.00550 **
## NS_CALLBELLRESPONSE             2.87e-01   4.28e-01    0.67  0.50299
## NS_NURSESATTITUDE               3.17e-01   5.45e-01    0.58  0.56100
## NS_NURSEPROACTIVENESS           5.26e-01   3.43e-01    1.53  0.12537
## OVS_OVERALLSTAFFPROMPTNESS     -4.34e-01   4.28e-01   -1.01  0.31138
## OVS_SECURITYATTITUDE            1.11e+00   4.17e-01    2.66  0.00793 **
## DP_DISCHARGETIME               -9.54e-01   4.33e-01   -2.20  0.02759 *
## DP_DISCHARGEQUERIES            -1.46e+00   4.43e-01   -3.29  0.00099 ***
## DP_DISCHARGEPROCESS             9.85e-01   5.44e-01    1.81  0.07021 .
## LengthofStay                   -1.85e-02   1.52e-02   -1.21  0.22492
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3257.3  on 4988  degrees of freedom
## Residual deviance: 2214.5  on 4939  degrees of freedom
## AIC: 2315
##
## Number of Fisher Scoring iterations: 6
```

```
summary(StepGlmModel)
```

```
##
## Call:
## glm(formula = Detractors ~ AgeYrs + Sex + Department + CE_ACCESSIBILITY +
##     CE_VALUEFORMONEY + EM_NURSING + AD_TIME + AD_TARRIFFPACKAGESEXPLAINATION +
##     INR_ROOMCLEANLINESS + FNB_FOODDELIVERYTIME + DOC_VISITS +
##     NS_NURSEPROACTIVENESS + OVS_SECURITYATTITUDE + DP_DISCHARGETIME +
##     DP_DISCHARGEQUERIES + DP_DISCHARGEPROCESS, family = "binomial",
##     data = LRTrain)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.008  -0.418  -0.211  -0.122   3.335
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     5.47841    0.48822   11.22  < 2e-16 ***
## AgeYrs                          0.00491    0.00324    1.51  0.13011
## SexM                            0.20149    0.11954    1.69  0.09188 .
## DepartmentGEN                   0.19799    0.24049    0.82  0.41036
## DepartmentGYNAEC                0.06896    0.33263    0.21  0.83576
## DepartmentORTHO                -0.14845    0.31252   -0.48  0.63478
## DepartmentPEDIATRIC             0.22075    0.31903    0.69  0.48898
## DepartmentRENAL                -0.71785    0.40763   -1.76  0.07823 .
## DepartmentSPECIAL              -0.21629    0.27026   -0.80  0.42355
## CE_ACCESSIBILITY               -2.30238    0.29381   -7.84  4.6e-15 ***
```

```
## CE_VALUEFORMONEY                  -3.99732    0.29752  -13.44  < 2e-16 ***
## EM_NURSING                        -1.35980    0.34707   -3.92  8.9e-05 ***
## AD_TIME                            0.58528    0.30855    1.90  0.05785 .
## AD_TARRIFFPACKAGESEXPLAINATION    -1.03883    0.33465   -3.10  0.00191 **
## INR_ROOMCLEANLINESS               -0.74028    0.27367   -2.70  0.00683 **
## FNB_FOODDELIVERYTIME              -0.82583    0.28185   -2.93  0.00339 **
## DOC_VISITS                        -1.28180    0.31469   -4.07  4.6e-05 ***
## NS_NURSEPROACTIVENESS              0.67057    0.25929    2.59  0.00970 **
## OVS_SECURITYATTITUDE               0.94306    0.37279    2.53  0.01141 *
## DP_DISCHARGETIME                  -0.90839    0.42549   -2.13  0.03277 *
## DP_DISCHARGEQUERIES               -1.53751    0.43216   -3.56  0.00037 ***
## DP_DISCHARGEPROCESS                0.95077    0.53591    1.77  0.07604 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3257.3  on 4988  degrees of freedom
## Residual deviance: 2233.9  on 4967  degrees of freedom
## AIC: 2278
##
## Number of Fisher Scoring iterations: 6
```

In the stepwise Regression model, the number of variables were reduced to 16.

The variables used in the Step-wise Regression Model are:

AgeYrs + Sex + Department + CE_ACCESSIBILITY + CE_VALUEFORMONEY + EM_NURSING + AD_TIME + AD_TARRIFFPACKAGESEXPLAINATION + INR_ROOMCLEANLINESS + FNB_FOODDELIVERYTIME + DOC_VISITS + NS_NURSEPROACTIVENESS + OVS_SECURITYATTITUDE + DP_DISCHARGETIME + DP_DISCHARGEQUERIES + DP_DISCHARGEPROCESS

Prediction and Confusion Matrix for Full Logistic Regression Model on Test Data

```
#Prediction accuracy of the Full logistic regression model:

pred <- predict(FullGlmModel, LRTest, type = "response")
pred.model <- rep("No", length(pred))
pred.model[pred > 0.5] <- "Yes"
confusionMatrix(table(pred.model, LRTest$Detractors), positive = "Yes")

## Confusion Matrix and Statistics
##
##
## pred.model  No Yes
##        No  308  24
##        Yes  12  20
##
##                Accuracy : 0.901
##                  95% CI : (0.866, 0.93)
##     No Information Rate : 0.879
##     P-Value [Acc > NIR] : 0.1119
##
##                   Kappa : 0.473
##
##  Mcnemar's Test P-Value : 0.0668
```

```
##
##             Sensitivity : 0.4545
##             Specificity : 0.9625
##          Pos Pred Value : 0.6250
##          Neg Pred Value : 0.9277
##              Prevalence : 0.1209
##          Detection Rate : 0.0549
##    Detection Prevalence : 0.0879
##       Balanced Accuracy : 0.7085
##
##        'Positive' Class : Yes
##
```

Prediction Accuracy for Full Logistic Regression model comes out to be 90.1%

Prediction and Confusion Matrix for Step-wise Logistic Regression on Test Data

```r
# Prediction accuracy of the stepwise logistic regression model:

pred <- predict(StepGlmModel, LRTest, type = "response")
pred.model <- rep("No", length(pred))
pred.model[pred > 0.5] <- "Yes"
confusionMatrix(table(pred.model, LRTest$Detractors), positive = "Yes")
```

```
## Confusion Matrix and Statistics
##
##
## pred.model  No Yes
##        No  308  24
##        Yes  12  20
##
##                Accuracy : 0.901
##                  95% CI : (0.866, 0.93)
##     No Information Rate : 0.879
##     P-Value [Acc > NIR] : 0.1119
##
##                   Kappa : 0.473
##
##  Mcnemar's Test P-Value : 0.0668
##
##             Sensitivity : 0.4545
##             Specificity : 0.9625
##          Pos Pred Value : 0.6250
##          Neg Pred Value : 0.9277
##              Prevalence : 0.1209
##          Detection Rate : 0.0549
##    Detection Prevalence : 0.0879
##       Balanced Accuracy : 0.7085
##
##        'Positive' Class : Yes
```

Prediction Accuracy for Step-wise Logistic Regression model comes out to be 90.1%

This is same as the full model, but it has very few variables(16 variables) as compared to the full model. Thus, the Step wise model avoids overfitting to the training data.

7.

With the help of ensemble methods, we want to identify the Detractors and Promotors among the customers. And we also want to understand why a customer is falling in any of the 3 profiles of Promotor, Detractor or Passive.

The variable CE_NPS is removed from the predictor variables, because in a sense it is our target variable, since we determine the NPS_Status of a customer on the basis of their NPS Score, i.e., NPS Score of 0-6 is Detractor, 7-8 is Passive and 9-10 is Promotor.

Note: I tried running the models with the variable CE_NPS, and the accuracy of those model came to be 1. On checking the important variables through importance function, I found that CE_NPS has a very high Mean Decrease Gini (~2000). But the model was not much informative of other important variables responsible for the given NPS Score / Status. Hence, I decided to remove CE_NPS from the predictors.

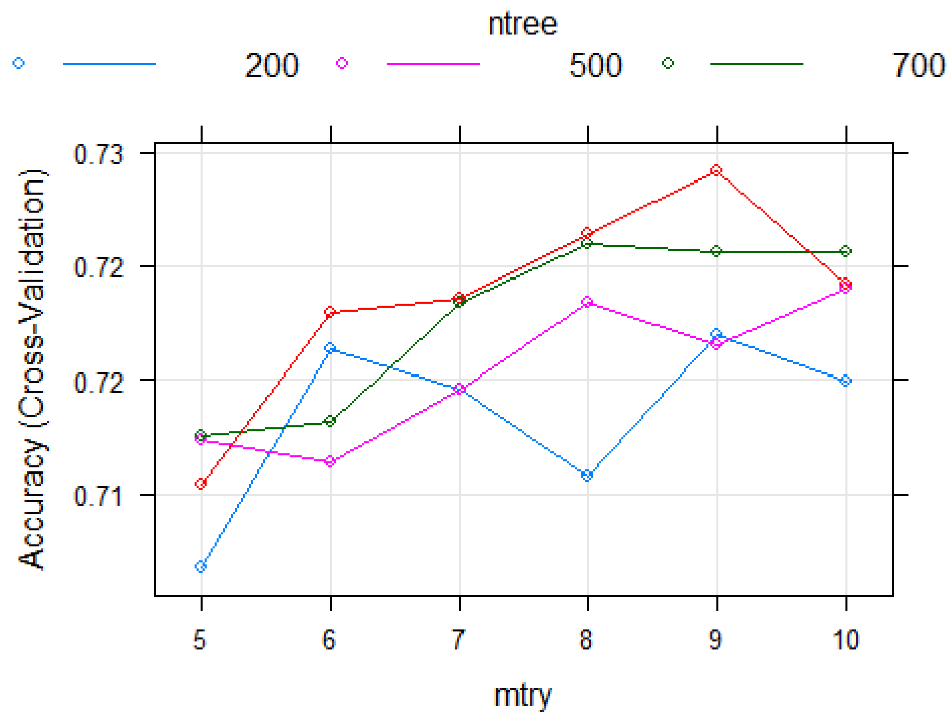
Random Forest for Multi-class Classification:

```
multirfTrain <- MultiTrain %>% select(-CE_NPS)
multirfTest <- MultiTest %>% select(-CE_NPS)
RFdata <- rbind(multirfTrain,multirfTest)

rfData_cat <- dplyr::select_if(RFdata, is.factor)
sapply(rfData_cat, function(x) length(unique(x)))

##    MaritalStatus              Sex      BedCategory       Department
##                5                2               11                7
## InsPayorcategory            State          Country        STATEZONE
##                5               58               29                7
##       NPS_Status
##                3

#We remove variables that have number of classes more than 53.

RFdata <- RFdata %>%
  select(-State)

multirfTrain <- multirfTrain %>%
  select(-State)

multirfTest <- multirfTest %>%
  select(-State)

# Setting the number of levels of factor variables in Training & Test data as same

common <- intersect(names(multirfTrain), names(multirfTest))
for (p in common) {
  if (class(multirfTrain[[p]]) == "factor") {
    levels(multirfTest[[p]]) <- levels(multirfTrain[[p]]) } }
```

Random Forest for Multi Class Classification:

Step 1: Cross Validation for Parameter Tuning best mtry and ntree

```
library(randomForest)
library(caret)

set.seed(101)
MHE_rf <- list(type = "Classification", library = "randomForest", loop = NULL)

MHE_rf$parameters <- data.frame(parameter = c("mtry", "ntree"), class = rep("numeric", 2)
, label = c("mtry", "ntree"))

MHE_rf$grid <- function(x, y, len = NULL, search = "grid") {}
MHE_rf$fit <- function(x, y, wts, param, lev, last, weights, classProbs, ...)
  {
  randomForest(x, y, mtry = param$mtry, ntree=param$ntree, ...)
  }

MHE_rf$predict <- function(modelFit, newdata, preProc = NULL, submodels = NULL) predict(m
odelFit, newdata)

MHE_rf$prob <- function(modelFit, newdata, preProc = NULL, submodels = NULL)

  predict(modelFit, newdata, type = "prob")

MHE_rf$sort <- function(x) x[order(x[,1]),]

MHE_rf$levels <- function(x) x$classes

control <- trainControl(method="cv", number=3)
tunegrid <- expand.grid(.mtry=c(5:10), .ntree=c(100,200,500,700))

set.seed(111)

multiRF <- train(NPS_Status ~.-NPS_Status, data=multirfTrain,
                   method=MHE_rf, metric="Accuracy",
                   tuneGrid=tunegrid, trControl=control)

plot(multiRF)
```




```
multiRF

## 4989 samples
##   45 predictor
##    3 classes: 'Detractor', 'Passive', 'Promotor'
##
## No pre-processing
## Resampling: Cross-Validated (3 fold)
## Summary of sample sizes: 3326, 3326, 3326
## Resampling results across tuning parameters:
##
##   mtry  ntree  Accuracy  Kappa
##    5    100    0.71      0.35
##    5    200    0.71      0.36
##    5    500    0.71      0.36
##    5    700    0.71      0.36
##    6    100    0.72      0.38
##    6    200    0.71      0.37
##    6    500    0.71      0.37
##    6    700    0.72      0.38
##    7    100    0.71      0.38
##    7    200    0.71      0.38
##    7    500    0.72      0.39
##    7    700    0.72      0.39
##    8    100    0.71      0.38
##    8    200    0.72      0.39
##    8    500    0.72      0.40
##    8    700    0.72      0.40
##    9    100    0.72      0.40
##    9    200    0.72      0.39
##    9    500    0.72      0.40
##    9    700    0.72      0.41
```

```
##   10    100    0.71      0.39
##   10    200    0.72      0.40
##   10    500    0.72      0.40
##   10    700    0.72      0.40

## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were mtry = 9 and ntree = 700.
```

Accuracy is highest for mtry = 9 and ntree = 700, with corresponding accuracy around ~72%.

Random Forest for Multi Class: Cross Validation for Model Evaluation –

I conducted a 10-fold cross validation and find out the accuracy of Random Forest for Multi-class classification problem, with the best mtry = 9 and best ntree = 700.

```
set.seed(111)
library(e1071)
library(pROC)
library(randomForest)
library(caret)
library(AUC)

k1 = 10

n = floor(nrow(RFdata)/k1)
accuracy.vect = rep(NA,k1)

for (i in 1:k1) {


  s1 = ((i-1) * n+1)
  s2 = (i*n)
  subset = s1:s2

  multirfcv.train = RFdata[-subset,]
  multirfcv.test = RFdata[subset,]

  tuned.RandForest <- randomForest(NPS_Status~.-NPS_Status, data = multirfcv.train, mtry
= 9, ntree = 700 )

  tuned.RF.pred <- predict(tuned.RandForest,
                          newdata = multirfcv.test, type = "class")

  accuracy.vect[i] <- (confusionMatrix(tuned.RF.pred, multirfcv.test$NPS_Status))$overall
[1]

 print(paste("Accuracy for fold", i, ":", accuracy.vect[i]))

    }

## [1] "Accuracy for fold 1 : 0.723364485981308"
## [1] "Accuracy for fold 2 : 0.738317757009346"
## [1] "Accuracy for fold 3 : 0.71588785046729"
## [1] "Accuracy for fold 4 : 0.753271028037383"
## [1] "Accuracy for fold 5 : 0.685981308411215"
```

```
## [1] "Accuracy for fold 6 : 0.700934579439252"
## [1] "Accuracy for fold 7 : 0.74018691588785"
## [1] "Accuracy for fold 8 : 0.730841121495327"
## [1] "Accuracy for fold 9 : 0.725233644859813"
## [1] "Accuracy for fold 10 : 0.695327102803738"
```

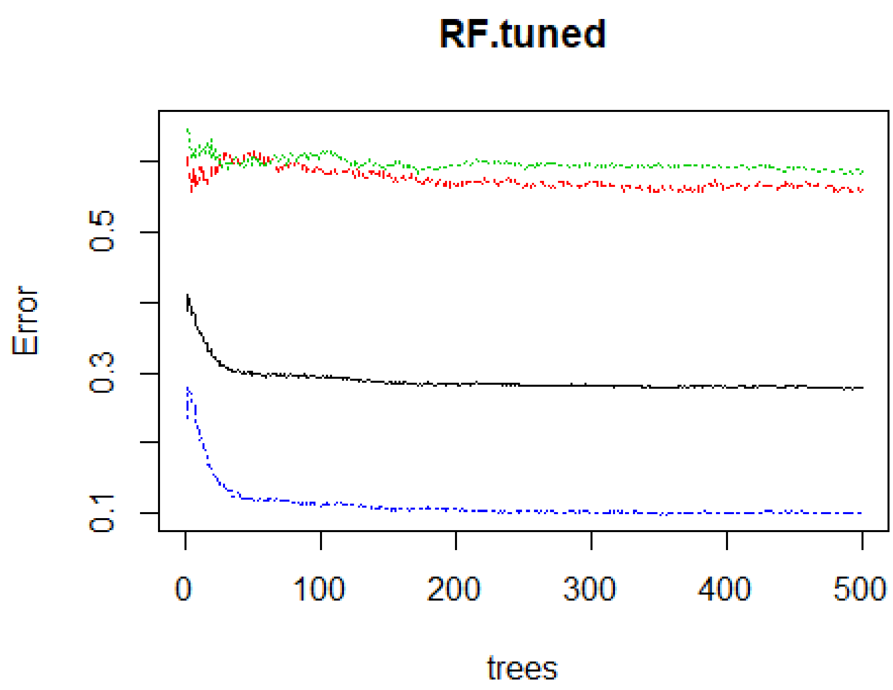
```
print(paste(" Average Accuracy for multiclass Random Forest :", mean(accuracy.vect)))
```

```
## [1] "Average Accuracy for multiclass Random Forest : 0.720934579439252"
```

Average Accuracy from 10-Fold cross Validation for multiclass Random Forest : 0.720934579439252

Retrain the model with best parameters obtained from Cross Validation and checking the performance measure - Accuracy on the test data.

```
set.seed(123)

#Retraining the model with best values of mtry and ntree

RF.tuned <- randomForest(NPS_Status ~. -NPS_Status,
                      data=multirfTrain,
                      importance = TRUE,
                      mtry = 9,
                      ntree = 500)
print(RF.tuned)
## Call:
##  randomForest(formula = NPS_Status ~ . - NPS_Status, data = multirfTrain,      importa
nce = TRUE, mtry = 9, ntree = 500)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 9
##
##         OOB estimate of  error rate: 28%
## Confusion matrix:
##           Detractor Passive Promotor class.error
## Detractor       221     148      133        0.56
## Passive          70     560      717        0.58
## Promotor         19     300     2821        0.10

plot(RF.tuned)
```



Prediction and Confusion Matrix for Multi-class Random Forest on Test Data

```
# Making final prediction on test data

RFtest.pred <- predict(RF.tuned, multirfTest, type = "prob")

confusionMatrix(predict(RF.tuned, newdata= multirfTest, type = "class"),
                multirfTest$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   Detractor Passive Promotor
##   Detractor         20       8        1
##   Passive           15      46       18
##   Promotor           9      63      184
##
## Overall Statistics
##
##                Accuracy : 0.687
##                  95% CI : (0.636, 0.734)
##     No Information Rate : 0.558
##     P-Value [Acc > NIR] : 3.12e-07
##
##                   Kappa : 0.407
##
##  Mcnemar's Test P-Value : 2.49e-07
##
## Statistics by Class:
##
##                         Class: Detractor Class: Passive Class: Promotor
## Sensitivity                       0.4545          0.393           0.906
```

```
## Specificity                    0.9719         0.866         0.553
## Pos Pred Value                 0.6897         0.582         0.719
## Neg Pred Value                 0.9284         0.751         0.824
## Prevalence                     0.1209         0.321         0.558
## Detection Rate                 0.0549         0.126         0.505
## Detection Prevalence           0.0797         0.217         0.703
## Balanced Accuracy              0.7132         0.630         0.730
```

Accuracy for multiclass Random Forest on Test Data : 68.7%

Important variables from multi-class Random Forest Model:

```
multirfImportant <- importance(RF.tuned, type = 2)

multiRFImportance <- data.frame(Variables = row.names(multirfImportant),
            Importance = round(multirfImportant[ ,'MeanDecreaseGini'],2))

multiRFImportance <- multiRFImportance[order((multiRFImportance$Importance),decreasing =
TRUE), ]

head(multiRFImportance, 20)

##                                                   Variables Importance
## AgeYrs                                               AgeYrs        213
## Estimatedcost                                 Estimatedcost        170
## CE_VALUEFORMONEY                           CE_VALUEFORMONEY        160
## CE_CSAT                                             CE_CSAT        158
## LengthofStay                                   LengthofStay        137
## BedCategory                                     BedCategory        128
## Department                                       Department        120
## InsPayorcategory                           InsPayorcategory         81
## CE_ACCESSIBILITY                           CE_ACCESSIBILITY         77
## AE_ATTENDEEFOOD                             AE_ATTENDEEFOOD         66
## AD_TARRIFFPACKAGESEXPLAINATION AD_TARRIFFPACKAGESEXPLAINATION         57
## DP_DISCHARGETIME                           DP_DISCHARGETIME         56
## FNB_FOODDELIVERYTIME                   FNB_FOODDELIVERYTIME         55
## DP_DISCHARGEPROCESS                     DP_DISCHARGEPROCESS         55
## FNB_FOODQUALITY                             FNB_FOODQUALITY         53
## INR_ROOMCLEANLINESS                     INR_ROOMCLEANLINESS         47
## DP_DISCHARGEQUERIES                     DP_DISCHARGEQUERIES         46
## AD_TIME                                             AD_TIME         46
## INR_ROOMAMBIENCE                           INR_ROOMAMBIENCE         45
## FNB_DIETICIAN                                 FNB_DIETICIAN         42
```

Final Results for Random Forest for Multi Class Classification:

CV for Parameter Tuning	10-fold CV for model evaluation	Accuracy on Test Data
mtry = 9, ntree = 700	Average Accuracy = 72.09%	Accuracy = 68.7%

AdaBoost for Multi Class Classification

```
multiAdaTrain <- MultiTrain %>% select(-CE_NPS)
multiAdaTest <- MultiTest %>% select(-CE_NPS)

multiAdaData <- rbind(multiAdaTrain,multiAdaTest)

# Creating dummy variables for categorical variables

library(caret)
multiAda_nums <- dplyr::select_if(multiAdaData, is.numeric)
multiAda_cat <- dplyr::select_if(multiAdaData, is.factor)

var_onehot <- c('MaritalStatus','Sex','BedCategory','Department', "InsPayorcategory", "St
ate", "Country", "STATEZONE")

# One Hot Encoding

dummys <- dummyVars(" ~ .", data = multiAda_cat[,var_onehot])

dummy_cats <- data.frame(predict(dummys, newdata = multiAda_cat[,var_onehot]))

 new.multiAdaData <- cbind(multiAda_nums,dummy_cats,multiAda_cat$NPS_Status)

names(new.multiAdaData)[names(new.multiAdaData) =="multiAda_cat$NPS_Status"] <- "NPS_Stat
us"

multiAdaTrain <- new.multiAdaData[1:4989,]

multiAdaTest <- new.multiAdaData[4990:5353,]

# Setting the number of levels of factor variables in Training & Test data as same

common <- intersect(names(multiAdaTrain), names(multiAdaTest))
for (p in common) {
  if (class(multiAdaTrain[[p]]) == "factor") {
    levels(multiAdaTest[[p]]) <- levels(multiAdaTrain[[p]]) } }
```

Ada Boost for Multi Class Classification:

Cross Validation for Parameter Tuning - Cross validation is conducted to find the best value of mfinal (no. of iterations), Complexity parameter (cp) and maxdepth.

```
set.seed(111)
library("adabag")

## Loading required package: rpart

## Loading required package: foreach

##
## Attaching package: 'foreach'

## The following objects are masked from 'package:purrr':
##
##     accumulate, when
```

```
## Loading required package: doParallel

## Loading required package: iterators

## Loading required package: parallel

# Find the best model with the best mfinal, cp and maxdepth, via cross-validations

multi.best.mfinal <- NA
multi.best.cp <- NA
multi.best.maxdepth <- NA

highest.accuracy <- 0
for (m.final in c(10,20)) {
  for (comp.p in c(0.005,0.001,0.01)) {
    for (maxdepth in c(10, 20,30)){
    multiAdaBoost <- boosting(NPS_Status ~ ., data = multiAdaTrain,
                              mfinal = m.final,
                              control = rpart.control(maxdepth =maxdepth,
                                                      cp=comp.p))

    multipred.best <- as.factor((predict.boosting(multiAdaBoost,multiAdaTrain))$class)

    #levels(multipred.best)
    #levels(multiAdaTrain$NPS_Status)

    fold.accuracy <- (confusionMatrix(multipred.best, multiAdaTrain$NPS_Status)$overall)[
1]

    cat("Results for mfinal=",m.final," : ", "Complexity parameter = ",comp.p,":", "and m
axdepth = ",maxdepth,":", "Accuracy = ",fold.accuracy,"\n",sep="")

    if(fold.accuracy > highest.accuracy){
      highest.accuracy <- fold.accuracy
      multi.best.mfinal <- m.final
      multi.best.cp <- comp.p
      multi.best.maxdepth <- maxdepth

    }
  }
 }
}

## Results for mfinal=10 : Complexity parameter = 0.005:and maxdepth = 10:Accuracy = 0.72
## Results for mfinal=10 : Complexity parameter = 0.005:and maxdepth = 20:Accuracy = 0.73
## Results for mfinal=10 : Complexity parameter = 0.005:and maxdepth = 30:Accuracy = 0.73
## Results for mfinal=10 : Complexity parameter = 0.001:and maxdepth = 10:Accuracy = 0.78
## Results for mfinal=10 : Complexity parameter = 0.001:and maxdepth = 20:Accuracy = 0.86
## Results for mfinal=10 : Complexity parameter = 0.001:and maxdepth = 30:Accuracy = 0.87
## Results for mfinal=10 : Complexity parameter = 0.01:and maxdepth = 10:Accuracy = 0.71
## Results for mfinal=10 : Complexity parameter = 0.01:and maxdepth = 20:Accuracy = 0.7
## Results for mfinal=10 : Complexity parameter = 0.01:and maxdepth = 30:Accuracy = 0.72
## Results for mfinal=20 : Complexity parameter = 0.005:and maxdepth = 10:Accuracy = 0.73
## Results for mfinal=20 : Complexity parameter = 0.005:and maxdepth = 20:Accuracy = 0.73
## Results for mfinal=20 : Complexity parameter = 0.005:and maxdepth = 30:Accuracy = 0.73
## Results for mfinal=20 : Complexity parameter = 0.001:and maxdepth = 10:Accuracy = 0.8
```

```
## Results for mfinal=20 : Complexity parameter = 0.001:and maxdepth = 20:Accuracy = 0.94
## Results for mfinal=20 : Complexity parameter = 0.001:and maxdepth = 30:Accuracy = 0.95
## Results for mfinal=20 : Complexity parameter = 0.01:and maxdepth = 10:Accuracy = 0.71
## Results for mfinal=20 : Complexity parameter = 0.01:and maxdepth = 20:Accuracy = 0.71
## Results for mfinal=20 : Complexity parameter = 0.01:and maxdepth = 30:Accuracy = 0.71

cat("For Multi-class Classification:", "\n")

## For Multi-class Classification:

cat("Best mfinal (number of iterations) is:",m.final,"\n")

## Best mfinal (number of iterations) is: 20

cat("Best complexity parameter is:",comp.p,"\n")

## Best complexity parameter is: 0.001

cat("Best maxdepth is:",maxdepth,"\n")

## Best maxdepth is: 30

cat("Best accuracy is:",highest.accuracy,"\n")

## Best accuracy is: 0.95
```

For Adaboost Multi-class Classification:
Best mfinal = 20
Best Complexity Parameter = 0.001
Best maxdepth = 30
Best accuracy = 0.95

I am using complexity parameter as 0.005, as a lower complexity parameter may result in overfitting and cause greater test error.

Retraining the model with best parameters obtained from cross validation

```
set.seed(111)
  library("adabag")

bestmulti.adaboost <- boosting(NPS_Status ~ ., data = multiAdaTrain, mfinal = 20, control
= rpart.control(maxdepth = 30, cp=0.005 ))
```

Prediction and Confusion Matrix for Multi-class Adaboost on Training Data

```
multi.predboosting.tr <- as.factor(predict.boosting(bestmulti.adaboost,
                                      newdata = multiAdaTrain)$class)
confusionMatrix(multi.predboosting.tr, multiAdaTrain$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Detractor Passive Promotor
##   Detractor       218      64       15
##   Passive         124     543      208
##   Promotor        160     740     2917
##
## Overall Statistics
##
##                Accuracy : 0.737
##                  95% CI : (0.725, 0.749)
##     No Information Rate : 0.629
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.435
##
##  Mcnemar's Test P-Value : <2e-16
##
## Statistics by Class:
##
##                       Class: Detractor Class: Passive Class: Promotor
## Sensitivity                     0.4343          0.403           0.929
## Specificity                     0.9824          0.909           0.513
## Pos Pred Value                  0.7340          0.621           0.764
## Neg Pred Value                  0.9395          0.805           0.810
## Prevalence                      0.1006          0.270           0.629
## Detection Rate                  0.0437          0.109           0.585
## Detection Prevalence            0.0595          0.175           0.765
## Balanced Accuracy               0.7083          0.656           0.721
```

Accuracy for multiclass Ada-Boost on Training Data : 73.7%

Prediction and Confusion Matrix for Multi-class Adaboost Model on Test Data

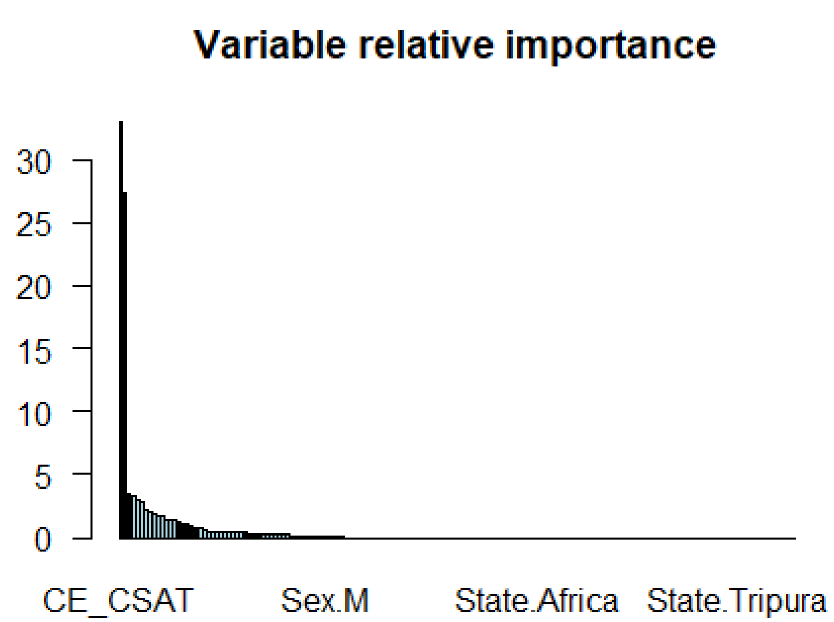
```
multi.predboosting <- as.factor(predict.boosting(bestmulti.adaboost,
                                      newdata = multiAdaTest)$class)
#length(multi.predboosting)
#length(multiAdaTest$NPS_Status)

confusionMatrix(multi.predboosting, multiAdaTest$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Detractor Passive Promotor
```

```
##   Detractor        20       9        2
##   Passive           8      41       17
##   Promotor         16      67      184
##
## Overall Statistics
##
##                Accuracy : 0.673
##                  95% CI : (0.622, 0.721)
##     No Information Rate : 0.558
##     P-Value [Acc > NIR] : 4.56e-06
##
##                   Kappa : 0.374
##
##  Mcnemar's Test P-Value : 7.54e-09
##
## Statistics by Class:
##
##                      Class: Detractor Class: Passive Class: Promotor
## Sensitivity                    0.4545          0.350           0.906
## Specificity                    0.9656          0.899           0.484
## Pos Pred Value                 0.6452          0.621           0.689
## Neg Pred Value                 0.9279          0.745           0.804
## Prevalence                     0.1209          0.321           0.558
## Detection Rate                 0.0549          0.113           0.505
## Detection Prevalence           0.0852          0.181           0.734
## Balanced Accuracy              0.7101          0.625           0.695
```

Accuracy for multiclass Ada-Boost on Test Data : 67.3%

Important variables from multi-class Adaboost Model:

```
importanceplot(bestmulti.adaboost)
```



```r
MultiadaImportant <- bestmulti.adaboost$importance

head(sort(MultiadaImportant, decreasing = TRUE),30)

##                     CE_CSAT                   CE_VALUEFORMONEY
##                     32.9684                            27.3753
##          DP_DISCHARGEQUERIES               BedCategory.GENERAL
##                      3.4338                             3.3482
##            CE_ACCESSIBILITY                             AgeYrs
##                      2.9343                             2.7836
##         FNB_FOODDELIVERYTIME                    AE_ATTENDEEFOOD
##                      2.1733                             2.0390
##             FNB_FOODQUALITY      AD_TARRIFFPACKAGESEXPLAINATION
##                      1.9280                             1.7477
##            INR_ROOMAMBIENCE                DP_DISCHARGEPROCESS
##                      1.7392                             1.3804
##                  DOC_VISITS                  FNB_STAFFATTITUDE
##                      1.3470                             1.3373
##            DP_DISCHARGETIME               AE_PATIENTSTATUSINFO
##                      1.2698                             1.0963
##         INR_ROOMCLEANLINESS                      Estimatedcost
##                      1.0272                             0.9344
##             AE_ATTENDEECARE                          EM_DOCTOR
##                      0.6974                             0.6705
##    OVS_OVERALLSTAFFATTITUDE            BedCategory.SEMISPECIAL
##                      0.5532                             0.4574
##            AD_STAFFATTITUDE        OVS_OVERALLSTAFFPROMPTNESS
##                      0.4468                             0.4432
##       NS_NURSEPROACTIVENESS         DOC_TREATMENTEFFECTIVENESS
##                      0.4401                             0.4252
##               FNB_DIETICIAN                       DOC_ATTITUDE
##                      0.4241                             0.4202
##                  EM_NURSING             EM_IMMEDIATEATTENTION
##                      0.3875                             0.3858
##           NS_NURSESATTITUDE                BedCategory.SPECIAL
##                      0.3574                             0.3164
##              STATEZONE.EAST        InsPayorcategory.INSURANCE
##                      0.2560                             0.2461
##                  EM_OVERALL                NS_CALLBELLRESPONSE
##                      0.2304                             0.2230
##              Department.GEN                    STATEZONE.SOUTH
##                      0.2230                             0.2230
##               INR_ROOMPEACE                  NS_NURSEPATIENCE
##                      0.1959                             0.1779
```

Final Results from Multi-Class Ada-Boost:

Parameter Tuning	Training accuracy with best parameters	Accuracy on Test Data
mfinal = 20, cp = 0.001, maxdepth = 30	**Average Accuracy = 73.7%**	**Accuracy = 67.3%**

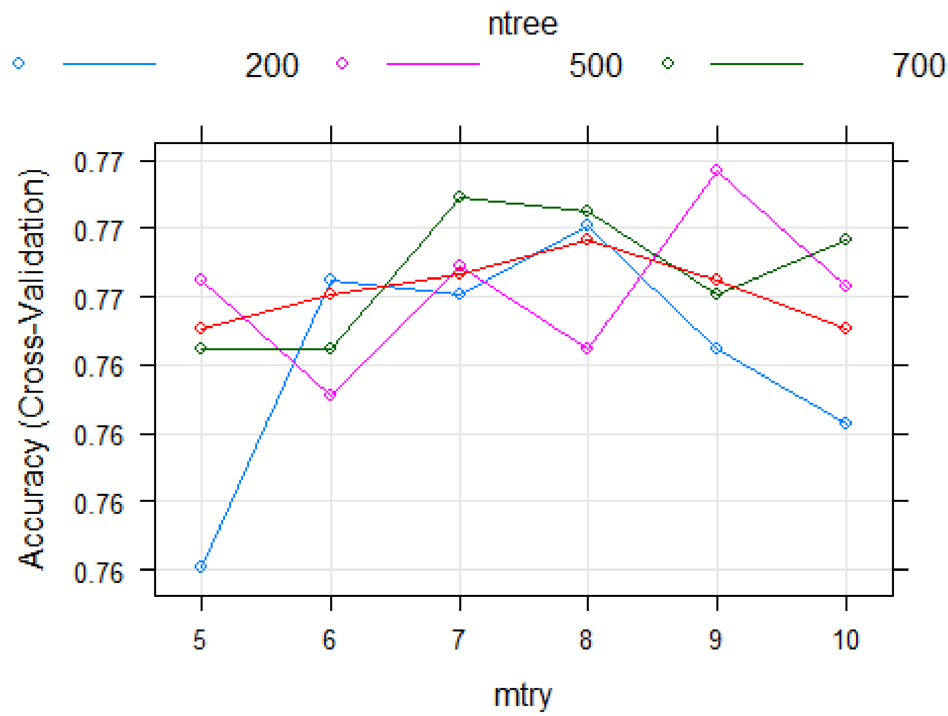
Random Forest for Binary classification:

```
binaryrf.train <- binaryTrain %>% select(-CE_NPS)

binaryrf.test <- binaryTest %>% select(-CE_NPS)

binaryrf.data <- rbind(binaryrf.train,binaryrf.test)


#We remove variables that have number of classes more than 53.

binaryrf.data <- binaryrf.data %>%
  select(-State)

binaryrf.train <- binaryrf.train %>%
  select(-State)

binaryrf.test <- binaryrf.test %>%
  select(-State)

# Setting the number of levels of factor variables in Training & Test data as same

common <- intersect(names(binaryrf.train), names(binaryrf.test))
for (p in common) {
  if (class(binaryrf.train[[p]]) == "factor") {
    levels(binaryrf.test[[p]]) <- levels(binaryrf.train[[p]]) } }
```

Random Forest for Binary classification:

Parameter Tuning for best mtry and ntree:

```


#Tuning Parameters for Binary class Random Forest

set.seed(111)

BinaryRF <- train(NPS_Status ~.-NPS_Status, data=binaryrf.train,
                   method=MHE_rf, metric="Accuracy",
                   tuneGrid=tunegrid, trControl=control)

plot(BinaryRF)
```




```
BinaryRF

## 4989 samples
##   45 predictor
##    2 classes: 'Detractor', 'Promotor'
##
## No pre-processing
## Resampling: Cross-Validated (3 fold)
## Summary of sample sizes: 3326, 3326, 3326
## Resampling results across tuning parameters:
##
##   mtry  ntree  Accuracy  Kappa
##    5    100    0.76      0.45
##    5    200    0.77      0.47
##    5    500    0.76      0.47
##    5    700    0.77      0.47
##    6    100    0.77      0.47
##    6    200    0.76      0.47
##    6    500    0.76      0.47
##    6    700    0.77      0.47
##    7    100    0.77      0.48
##    7    200    0.77      0.47
##    7    500    0.77      0.48
##    7    700    0.77      0.47
##    8    100    0.77      0.48
##    8    200    0.76      0.47
##    8    500    0.77      0.48
##    8    700    0.77      0.48
##    9    100    0.76      0.47
##    9    200    0.77      0.48
##    9    500    0.77      0.48
##    9    700    0.77      0.48
```

```
##   10    100    0.76      0.47
##   10    200    0.77      0.48
##   10    500    0.77      0.48
##   10    700    0.77      0.47
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were mtry = 9 and ntree = 200.
```

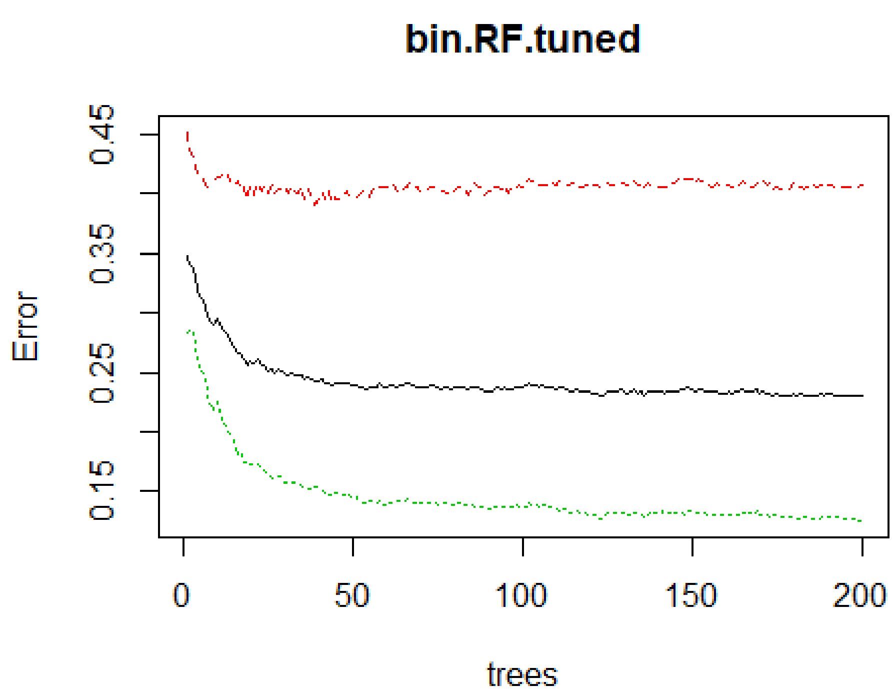
Binary Random Forest: Accuracy is highest for mtry = 9 and ntree = 200, with corresponding accuracy around ~77%.

```
set.seed(111)

k2 = 10

n = floor(nrow(binaryrf.data)/k2)
accuracy.vect.bin = rep(NA,k2)

for (i in 1:k2) {

  s3 = ((i-1) * n+1)
  s4 = (i*n)
  subset = s3:s4

  binrfcv.train = binaryrf.data[-subset,]
  binrfcv.test = binaryrf.data[subset,]

  Bin.tuned.RandForest <- randomForest(NPS_Status~.-NPS_Status, data = binrfcv.train, mtr
y = 9, ntree = 200 )

  binRF.pred <- predict(Bin.tuned.RandForest,
                           newdata = binrfcv.test, type = "class")

  accuracy.vect.bin[i] <- (confusionMatrix(binRF.pred, binrfcv.test$NPS_Status))$overall[
1]

 print(paste("Accuracy for fold", i, ":", accuracy.vect.bin[i]))

    }

## [1] "Accuracy for fold 1 : 0.786915887850467"
## [1] "Accuracy for fold 2 : 0.779439252336449"
## [1] "Accuracy for fold 3 : 0.758878504672897"
## [1] "Accuracy for fold 4 : 0.794392523364486"
## [1] "Accuracy for fold 5 : 0.734579439252336"
## [1] "Accuracy for fold 6 : 0.753271028037383"
## [1] "Accuracy for fold 7 : 0.777570093457944"
## [1] "Accuracy for fold 8 : 0.790654205607477"
## [1] "Accuracy for fold 9 : 0.779439252336449"
## [1] "Accuracy for fold 10 : 0.747663551401869"

print(paste(" Average Accuracy for binary Random Forest :", mean(accuracy.vect.bin)))

## [1] " Average Accuracy for binary Random Forest : 0.770280373831776"
```

Average Accuracy from 10-Fold cross Validation for binary Random Forest : 0.770280373831776

Retrain the model with best parameters

```
set.seed(123)

#Retraining the model with best values of mtry and ntree

bin.RF.tuned <- randomForest(NPS_Status ~. -NPS_Status,
                      data=binaryrf.train,
                      importance = TRUE,
                      mtry = 9,
                      ntree = 200)
print(bin.RF.tuned)

##
## Call:
##  randomForest(formula = NPS_Status ~ . - NPS_Status, data = binaryrf.train,      impor
tance = TRUE, mtry = 9, ntree = 200)
##                Type of random forest: classification
##                      Number of trees: 200
## No. of variables tried at each split: 9
##
##         OOB estimate of  error rate: 23%
## Confusion matrix:
##           Detractor Promotor class.error
## Detractor      1095      754        0.41
## Promotor        394     2746        0.13

plot(bin.RF.tuned)
```



Prediction & Confusion Matrix for Binary class Random Forest on Test Data

```
# Making final prediction on test data

RFtest.pred <- predict(bin.RF.tuned, binaryrf.test, type = "prob")

confusionMatrix(predict(bin.RF.tuned, newdata= binaryrf.test,
                        type = "class"),
                binaryrf.test$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Detractor Promotor
##   Detractor        86       20
##   Promotor         75      183
##
##                Accuracy : 0.739
##                  95% CI : (0.691, 0.783)
##     No Information Rate : 0.558
##     P-Value [Acc > NIR] : 6.40e-13
##
##                   Kappa : 0.452
##
##  Mcnemar's Test P-Value : 3.02e-08
##
##             Sensitivity : 0.534
##             Specificity : 0.901
##          Pos Pred Value : 0.811
##          Neg Pred Value : 0.709
##              Prevalence : 0.442
##          Detection Rate : 0.236
##    Detection Prevalence : 0.291
##       Balanced Accuracy : 0.718
##
##        'Positive' Class : Detractor
##
```

Accuracy for Binary class Random Forest on Test Data : 73.9%

Important variables from binary-class Random Forest Model:

```
BinrfImportant <- importance(bin.RF.tuned, type = 2)

BinRFImportance <- data.frame(Variables = row.names(BinrfImportant),
            Importance = round(BinrfImportant[ ,'MeanDecreaseGini'],2))

BinRFImportance <- BinRFImportance[order((BinRFImportance$Importance),decreasing = TRUE),
]

head(BinRFImportance, 20)

##                                                        Variables Importance
## AgeYrs                                                    AgeYrs        186
## CE_VALUEFORMONEY                                CE_VALUEFORMONEY        163
## CE_CSAT                                                  CE_CSAT        161
## Estimatedcost                                      Estimatedcost        149
## BedCategory                                          BedCategory        121
## LengthofStay                                        LengthofStay        118
## Department                                            Department        107
## InsPayorcategory                                InsPayorcategory         72
## AE_ATTENDEEFOOD                                  AE_ATTENDEEFOOD         66
## DP_DISCHARGETIME                                DP_DISCHARGETIME         64
## DP_DISCHARGEPROCESS                          DP_DISCHARGEPROCESS         61
## CE_ACCESSIBILITY                                CE_ACCESSIBILITY         60
## FNB_FOODDELIVERYTIME                        FNB_FOODDELIVERYTIME         48
## AD_TARRIFFPACKAGESEXPLAINATION AD_TARRIFFPACKAGESEXPLAINATION         48
## FNB_FOODQUALITY                                  FNB_FOODQUALITY         47
## DP_DISCHARGEQUERIES                          DP_DISCHARGEQUERIES         44
## INR_ROOMAMBIENCE                                INR_ROOMAMBIENCE         43
## AD_TIME                                                  AD_TIME         40
## INR_ROOMPEACE                                      INR_ROOMPEACE         37
## INR_ROOMCLEANLINESS                          INR_ROOMCLEANLINESS         36
```

Final Results for Random Forest for Binary Class Classification:

CV for Parameter Tuning	10-fold CV for model evaluation	Accuracy on Test Data
mtry = 9, ntree = 200	**Average Accuracy = 77.02%**	**Accuracy = 73.9%**

Ada Boost for Binary Classification:

```r
binAdaTrain <- binaryTrain %>% select(-CE_NPS)

binAdaTest <- binaryTest %>% select(-CE_NPS)

binAdaData <- rbind(binAdaTrain,binAdaTest)

library(caret)
binAda_nums <- dplyr::select_if(binAdaData, is.numeric)
binAda_cat <- dplyr::select_if(binAdaData, is.factor)

# Creating dummy variables for categorical variables

var_onehot <- c('MaritalStatus','Sex','BedCategory','Department', "InsPayorcategory", "St
ate", "Country", "STATEZONE")

# One Hot Encoding

dummy <- dummyVars(" ~ .", data = binAda_cat[,var_onehot])

dummy_cat <- data.frame(predict(dummy, newdata = binAda_cat[,var_onehot]))

 new.binAdaData <- cbind(binAda_nums,dummy_cat,binAda_cat$NPS_Status)

names(new.binAdaData)[names(new.binAdaData) =="binAda_cat$NPS_Status"] <- "NPS_Status"

binAdaTrain <- new.binAdaData[1:4989,]

binAdaTest <- new.binAdaData[4990:5353,]

# Setting the number of levels of factor variables in Training & Test data as same

common <- intersect(names(binAdaTrain), names(binAdaTest))
for (p in common) {
  if (class(binAdaTrain[[p]]) == "factor") {
    levels(binAdaTest[[p]]) <- levels(binAdaTrain[[p]]) } }
```

Ada Boost for Binary Class Classification:

Cross Validation for Parameter Tuning - Cross validation is conducted to find the best value of mfinal (no. of iterations), Complexity parameter (cp) and maxdepth.

```r
# Find the best model with the best mfinal, cp and maxdepth, via cross-validations
set.seed(111)
bin.best.mfinal <- NA
bin.best.cp <- NA
bin.best.maxdepth <- NA

highestbin.accuracy <- 0
for (m.final1 in c(10,20)) {
  for (comp.p1 in c(0.005,0.001,0.01)) {
    for (maxdepth1 in c(10, 20,30)){
    binaryAdaBoost <- boosting(NPS_Status ~ ., data = binAdaTrain,
                              mfinal = m.final1,
```

```
                              control = rpart.control(maxdepth =maxdepth1,
                                                          cp=comp.p1))

    binpred.best <- as.factor((predict.boosting(binaryAdaBoost,binAdaTrain))$class)

    #levels(multipred.best)
    #levels(multiAdaTrain$NPS_Status)

    binfold.accuracy <- (confusionMatrix(binpred.best, binAdaTrain$NPS_Status)$overall)[1
]

    cat("Results in the Binary classification for mfinal=",m.final1," : ", "Complexity pa
rameter = ",comp.p1,":", "and maxdepth = ",maxdepth1,":", "Accuracy = ",binfold.accuracy,
"\n",sep="")

    if(binfold.accuracy > highest.accuracy){
      highestbin.accuracy <- binfold.accuracy
      multi.best.mfinal <- m.final1
      multi.best.cp <- comp.p1
      multi.best.maxdepth <- maxdepth1

    }
  }
 }
}

## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.005:and
maxdepth = 10:Accuracy = 0.78
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.005:and
maxdepth = 20:Accuracy = 0.79
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.005:and
maxdepth = 30:Accuracy = 0.79
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.001:and
maxdepth = 10:Accuracy = 0.83
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.001:and
maxdepth = 20:Accuracy = 0.93
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.001:and
maxdepth = 30:Accuracy = 0.93
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.01:and m
axdepth = 10:Accuracy = 0.76
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.01:and m
axdepth = 20:Accuracy = 0.77
## Results in the Binary classification for mfinal=10 : Complexity parameter = 0.01:and m
axdepth = 30:Accuracy = 0.77
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.005:and
maxdepth = 10:Accuracy = 0.79
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.005:and
maxdepth = 20:Accuracy = 0.8
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.005:and
maxdepth = 30:Accuracy = 0.8
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.001:and
maxdepth = 10:Accuracy = 0.86
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.001:and
maxdepth = 20:Accuracy = 0.98
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.001:and
maxdepth = 30:Accuracy = 1
```

```
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.01:and m
axdepth = 10:Accuracy = 0.77
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.01:and m
axdepth = 20:Accuracy = 0.78
## Results in the Binary classification for mfinal=20 : Complexity parameter = 0.01:and m
axdepth = 30:Accuracy = 0.77

cat("For Binary Classification:", "\n")

## For Binary Classification:

cat("Best mfinal (number of iterations) is:",m.final,"\n")

## Best mfinal (number of iterations) is: 20

cat("Best complexity parameter is:",comp.p,"\n")

## Best complexity parameter is: 0.001

cat("Best maxdepth is:",maxdepth,"\n")

## Best maxdepth is: 30

cat("Best accuracy is:",highestbin.accuracy,"\n")

## Best accuracy is: 1
```

For Adaboost Binary-class Classification:
Best mfinal = 20
Best Complexity Parameter = 0.001
Best maxdepth = 30
Best accuracy = 1

I am using complexity parameter as 0.005, as a lower complexity parameter may result in overfitting and cause greater test error.

Retraining the model with best parameters obtained from cross validation

```
set.seed(111)
  library("adabag")

bestbinary.adaboost <- boosting(NPS_Status ~ ., data = binAdaTrain, mfinal = 20, control
= rpart.control(maxdepth = 30, cp=0.005 ))
```

Prediction & Confusion Matrix for Binary class Ada-boost on Training Data

```
binary.predboosting.tr <- as.factor(predict.boosting(bestbinary.adaboost,
                                      newdata = binAdaTrain)$class)
#length(multi.predboosting)
#length(multiAdaTest$NPS_Status)

confusionMatrix(binary.predboosting.tr, binAdaTrain$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Detractor Promotor
##   Detractor      1134      258
##   Promotor        715     2882
##
##                Accuracy : 0.805
##                  95% CI : (0.794, 0.816)
##     No Information Rate : 0.629
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.56
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.613
##             Specificity : 0.918
##          Pos Pred Value : 0.815
##          Neg Pred Value : 0.801
##              Prevalence : 0.371
##          Detection Rate : 0.227
##    Detection Prevalence : 0.279
##       Balanced Accuracy : 0.766
##
##        'Positive' Class : Detractor
##
```

Accuracy for Binary class Ada-Boost on Training Data : 80.5%

Prediction & Confusion Matrix for Binary class Ada-boost on Test Data

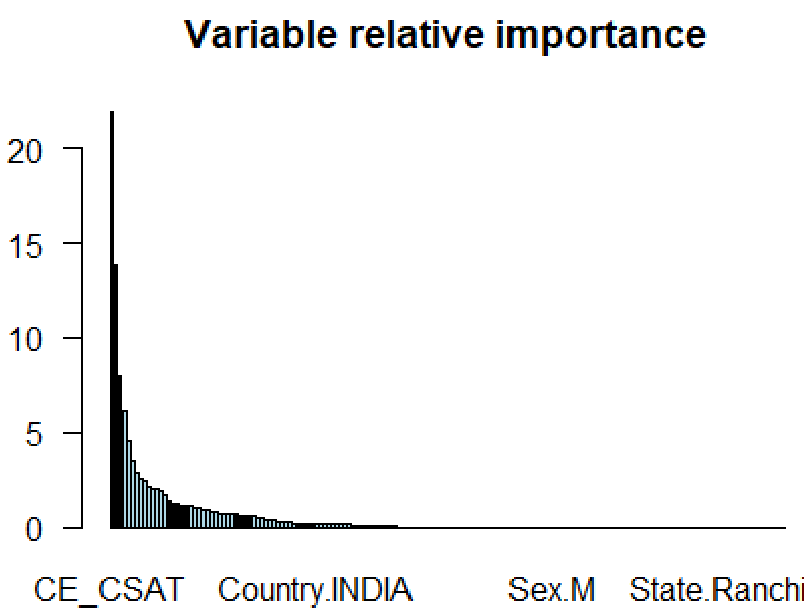
```
binary.predboosting <- as.factor(predict.boosting(bestbinary.adaboost,
                                      newdata = binAdaTest)$class)
#length(multi.predboosting)
#length(multiAdaTest$NPS_Status)

confusionMatrix(binary.predboosting, binAdaTest$NPS_Status)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Detractor Promotor
##   Detractor        87       29
##   Promotor         74      174
##
```

```
##                Accuracy : 0.717
##                  95% CI : (0.668, 0.763)
##     No Information Rate : 0.558
##     P-Value [Acc > NIR] : 2.83e-10
##
##                   Kappa : 0.409
##
##  Mcnemar's Test P-Value : 1.45e-05
##
##             Sensitivity : 0.540
##             Specificity : 0.857
##          Pos Pred Value : 0.750
##          Neg Pred Value : 0.702
##              Prevalence : 0.442
##          Detection Rate : 0.239
##    Detection Prevalence : 0.319
##       Balanced Accuracy : 0.699
##
##        'Positive' Class : Detractor
##
```

Accuracy for Binary class Random Forest on Test Data : 71.7%

Important Variables in Binary class Ada-boost Model

```
importanceplot(bestbinary.adaboost)
```




```
BinadaImportant <- bestbinary.adaboost$importance

head(sort(BinadaImportant, decreasing = TRUE),30)

##                           CE_CSAT                      CE_VALUEFORMONEY
##                            21.934                                13.826
##                    AE_ATTENDEEFOOD                                AgeYrs
##                             7.926                                 6.190
##                  CE_ACCESSIBILITY        AD_TARRIFFPACKAGESEXPLAINATION
##                             4.502                                 3.466
```

```
##                         Estimatedcost                         LengthofStay
##                                 2.831                                2.547
##                            DOC_VISITS                   BedCategory.GENERAL
##                                 2.369                                2.057
##                       FNB_FOODQUALITY                     AD_STAFFATTITUDE
##                                 2.018                                1.990
##                      INR_ROOMAMBIENCE                  FNB_FOODDELIVERYTIME
##                                 1.851                                1.636
##                  INR_ROOMCLEANLINESS                  DP_DISCHARGEPROCESS
##                                 1.388                                1.279
##                  AE_PATIENTSTATUSINFO               NS_NURSEPROACTIVENESS
##                                 1.239                                1.154
##                      AE_ATTENDEECARE                        DOC_ATTITUDE
##                                 1.143                                1.120
##                        INR_ROOMPEACE                     DP_DISCHARGETIME
##                                 1.045                                0.998
##                        Department.GEN                  NS_CALLBELLRESPONSE
##                                 0.959                                0.880
##                    INR_ROOMEQUIPMENT               EM_IMMEDIATEATTENTION
##                                 0.857                                0.841
##                   DP_DISCHARGEQUERIES                   FNB_STAFFATTITUDE
##                                 0.718                                0.717
##                 OVS_SECURITYATTITUDE                               Sex.F
##                                 0.700                                0.670
##          OVS_OVERALLSTAFFPROMPTNESS                              AD_TIME
##                                 0.659                                0.633
##                            EM_NURSING                    NS_NURSESATTITUDE
##                                 0.629                                0.590
```

Final Results from Binary Class Ada-Boost:

Parameter Tuning	Training accuracy with best parameters	Accuracy on Test Data
mfinal = 20, cp = 0.001, maxdepth = 30	**Average Accuracy = 80.5%**	**Accuracy = 71.7%**

8. Check the effect of balancing methods (under-sampling, over-sampling, and SMOTE (Synthethic Minority Oversampling) on the performance of ensemble methods.

Balancing Data using SMOTE:

Balancing the train data using SMOTE function from DMwR library. SMOTE uses K-nearest neighbour method to generate new samples, as to increase the minority class rows and decrease the majority class rows in the data.

```
Samplingtrain <- binaryTrain
Samplingtest <- binaryTest

Samplingtrain %>%
  group_by(NPS_Status) %>%
  summarise(count = n())

## # A tibble: 2 x 2
##   NPS_Status count
```

```
##   <fct>      <int>
## 1 Detractor   1849
## 2 Promotor    3140

library(DMwR)

## Smote : Synthetic Minority Oversampling Technique To Handle Class Imbalance In Binary
Classification

SMOTE.balanced <- SMOTE(NPS_Status ~., as.data.frame(Samplingtrain),
                       perc.under = 170,
                       perc.over = 180 , k = 5)
as.data.frame(table(SMOTE.balanced$NPS_Status))

##        Var1 Freq
## 1 Detractor 3698
## 2  Promotor 3143
```

Balancing Data using Under Sampling:

```
library(ROSE)

## Loaded ROSE 0.0-3

underSample <- ovun.sample(NPS_Status ~., as.data.frame(Samplingtrain),
                           method = "under", N=4000)$data
underSample %>% group_by(NPS_Status) %>% count()

## # A tibble: 2 x 2
## # Groups:   NPS_Status [2]
##   NPS_Status     n
##   <fct>      <int>
## 1 Promotor    2151
## 2 Detractor   1849
```

Balancing Data using Over Sampling:

```
library(ROSE)

overSample <- ovun.sample(NPS_Status ~., as.data.frame(Samplingtrain),
                          method = "over", N=6000)$data
overSample %>% group_by(NPS_Status) %>% count()

## # A tibble: 2 x 2
## # Groups:   NPS_Status [2]
##   NPS_Status     n
##   <fct>      <int>
## 1 Promotor    3140
## 2 Detractor   2860
```

Random Forest with SMOTE data:

```
rftrain.smote <- SMOTE.balanced %>% select(-CE_NPS)
rftest.smote <- binaryTest %>% select(-CE_NPS)

rf.smote <- rbind(rftrain.smote,rftest.smote)

rf.smote <- rf.smote %>% select(-State)

#rfsmote_cat <- dplyr::select_if(rf.smote, is.factor)
#sapply(rfsmote_cat, function(x) length(unique(x)))

set.seed(111)
k2 = 10
n = floor(nrow(rf.smote)/k2)
accuracy.vect.smote = rep(NA,k2)

for (i in 1:k2) {

  s5 = ((i-1) * n+1)
  s6 = (i*n)
  subset = s5:s6

  smoterfcv.train = rf.smote[-subset,]
  smoterfcv.test = rf.smote[subset,]

  smote.tuned.RandForest <- randomForest(NPS_Status~.-NPS_Status, data = smoterfcv.train,
mtry = 9, ntree = 200 )

  smoteRF.pred <- predict(smote.tuned.RandForest,
                          newdata = smoterfcv.test, type = "class")

  accuracy.vect.smote[i] <- (confusionMatrix(smoteRF.pred, smoterfcv.test$NPS_Status))$ov
erall[1]

 print(paste("Accuracy for fold", i, ":", accuracy.vect.smote[i]))

    }

## [1] "Accuracy for fold 1 : 0.891666666666667"
## [1] "Accuracy for fold 2 : 0.875"
## [1] "Accuracy for fold 3 : 0.894444444444444"
## [1] "Accuracy for fold 4 : 0.902777777777778"
## [1] "Accuracy for fold 5 : 0.766666666666667"
## [1] "Accuracy for fold 6 : 0.595833333333333"
## [1] "Accuracy for fold 7 : 0.716666666666667"
## [1] "Accuracy for fold 8 : 0.977777777777778"
## [1] "Accuracy for fold 9 : 0.970833333333333"
## [1] "Accuracy for fold 10 : 0.843055555555556"

print(paste(" Average Accuracy for Smote Random Forest :", mean(accuracy.vect.smote)))

## [1] " Average Accuracy for Smote Random Forest : 0.843472222222222"
```

Accuracy for Random Forest through Cross Validation, with SMOTE: 84.34%

Important Variables for Random Forest with SMOTE

```
smoterfImportant <- importance(smote.tuned.RandForest, type = 2)

smoteRFImportance <- data.frame(Variables = row.names(smoterfImportant),
            Importance = round(smoterfImportant[ ,'MeanDecreaseGini'],2))

smoteRFImportance <- smoteRFImportance[order((smoteRFImportance$Importance),decreasing =
TRUE), ]

head(smoteRFImportance, 20)

##                                                       Variables Importance
## CE_CSAT                                                 CE_CSAT        306
## CE_VALUEFORMONEY                               CE_VALUEFORMONEY        249
## AgeYrs                                                   AgeYrs        201
## Estimatedcost                                     Estimatedcost        173
## DP_DISCHARGETIME                               DP_DISCHARGETIME        139
## LengthofStay                                       LengthofStay        137
## BedCategory                                         BedCategory        130
## CE_ACCESSIBILITY                               CE_ACCESSIBILITY        130
## Department                                           Department        127
## DP_DISCHARGEPROCESS                         DP_DISCHARGEPROCESS        118
## AE_ATTENDEEFOOD                                 AE_ATTENDEEFOOD        108
## AD_TARRIFFPACKAGESEXPLAINATION AD_TARRIFFPACKAGESEXPLAINATION         98
## InsPayorcategory                               InsPayorcategory         86
## DP_DISCHARGEQUERIES                         DP_DISCHARGEQUERIES         71
## FNB_FOODQUALITY                                 FNB_FOODQUALITY         67
## AD_TIME                                                 AD_TIME         65
## STATEZONE                                             STATEZONE         63
## FNB_FOODDELIVERYTIME                       FNB_FOODDELIVERYTIME         56
## INR_ROOMPEACE                                     INR_ROOMPEACE         54
## FNB_DIETICIAN                                     FNB_DIETICIAN         49
```

Random Forest with Under Sampled data:

```
rftrain.us <- underSample %>% select(-CE_NPS)
rftest.us <- binaryTest %>% select(-CE_NPS)

rf.us <- rbind(rftrain.us,rftest.us)

rf.us <- rf.us %>% select(-State)

#rfsmote_cat <- dplyr::select_if(rf.smote, is.factor)
#sapply(rfsmote_cat, function(x) length(unique(x)))

set.seed(111)
k2 = 10

n = floor(nrow(rf.us)/k2)
accuracy.vect.us = rep(NA,k2)

for (i in 1:k2) {


  s7 = ((i-1) * n+1)
```

```
  s8 = (i*n)
  subset = s7:s8

  USrfcv.train = rf.us[-subset,]
  USrfcv.test = rf.us[subset,]

  US.tuned.RandForest <- randomForest(NPS_Status~.-NPS_Status, data = USrfcv.train, mtry
= 9, ntree = 200 )

  usRF.pred <- predict(US.tuned.RandForest,
                          newdata = USrfcv.test, type = "class")

  accuracy.vect.us[i] <- (confusionMatrix(usRF.pred, USrfcv.test$NPS_Status))$overall[1]

 print(paste("Accuracy for fold", i, ":", accuracy.vect.us[i]))

    }

## [1] "Accuracy for fold 1 : 0.782110091743119"
## [1] "Accuracy for fold 2 : 0.779816513761468"
## [1] "Accuracy for fold 3 : 0.756880733944954"
## [1] "Accuracy for fold 4 : 0.73394495412844"
## [1] "Accuracy for fold 5 : 0.786697247706422"
## [1] "Accuracy for fold 6 : 0.600917431192661"
## [1] "Accuracy for fold 7 : 0.630733944954128"
## [1] "Accuracy for fold 8 : 0.582568807339449"
## [1] "Accuracy for fold 9 : 0.658256880733945"
## [1] "Accuracy for fold 10 : 0.717889908256881"

print(paste(" Average Accuracy for Under Sampled Random Forest :", mean(accuracy.vect.us)
))

## [1] " Average Accuracy for Under Sampled Random Forest : 0.702981651376147"
```

Accuracy for Random Forest through Cross Validation, with Under Sampled Data: 70.29%

Important Variables for Random Forest with Under Sampled Data

```
usrfImportant <- importance(US.tuned.RandForest, type = 2)

usRFImportance <- data.frame(Variables = row.names(usrfImportant),
            Importance = round(usrfImportant[ ,'MeanDecreaseGini'],2))

usRFImportance <- usRFImportance[order((usRFImportance$Importance),decreasing = TRUE), ]

head(usRFImportance, 20)

##                                              Variables Importance
## AgeYrs                                          AgeYrs        158
## CE_CSAT                                        CE_CSAT        141
## Estimatedcost                            Estimatedcost        126
## CE_VALUEFORMONEY                      CE_VALUEFORMONEY        118
## LengthofStay                              LengthofStay         99
## BedCategory                                BedCategory         97
## Department                                  Department         92
## AE_ATTENDEEFOOD                        AE_ATTENDEEFOOD         70
## InsPayorcategory                      InsPayorcategory         63
```

```
## DP_DISCHARGETIME                                        DP_DISCHARGETIME         53
## DP_DISCHARGEPROCESS                                  DP_DISCHARGEPROCESS         51
## AD_TARRIFFPACKAGESEXPLAINATION AD_TARRIFFPACKAGESEXPLAINATION         51
## CE_ACCESSIBILITY                                        CE_ACCESSIBILITY         51
## FNB_FOODQUALITY                                          FNB_FOODQUALITY         45
## FNB_FOODDELIVERYTIME                                FNB_FOODDELIVERYTIME         42
## DP_DISCHARGEQUERIES                                  DP_DISCHARGEQUERIES         37
## AD_TIME                                                          AD_TIME         33
## FNB_DIETICIAN                                              FNB_DIETICIAN         32
## STATEZONE                                                      STATEZONE         30
## INR_ROOMCLEANLINESS                                  INR_ROOMCLEANLINESS         29
```

Random Forest with Over Sampled data:

```
rftrain.os <- overSample %>% select(-CE_NPS)
rftest.os <- binaryTest %>% select(-CE_NPS)

rf.os <- rbind(rftrain.os,rftest.os)

rf.os <- rf.os %>% select(-State)

#rfsmote_cat <- dplyr::select_if(rf.smote, is.factor)
#sapply(rfsmote_cat, function(x) length(unique(x)))

set.seed(111)
k2 = 10
n = floor(nrow(rf.os)/k2)
accuracy.vect.os = rep(NA,k2)

for (i in 1:k2) {

  s9 = ((i-1) * n+1)
  s10 = (i*n)
  subset = s9:s10

  OSrfcv.train = rf.os[-subset,]
  OSrfcv.test = rf.os[subset,]

  OS.tuned.RandForest <- randomForest(NPS_Status~.-NPS_Status, data = OSrfcv.train, mtry
= 9, ntree = 500 )

  osRF.pred <- predict(OS.tuned.RandForest,
                           newdata = OSrfcv.test, type = "class")

  accuracy.vect.os[i] <- (confusionMatrix(osRF.pred, OSrfcv.test$NPS_Status))$overall[1]

 print(paste("Accuracy for fold", i, ":", accuracy.vect.os[i]))

    }

## [1] "Accuracy for fold 1 : 0.861635220125786"
## [1] "Accuracy for fold 2 : 0.845911949685535"
## [1] "Accuracy for fold 3 : 0.842767295597484"
## [1] "Accuracy for fold 4 : 0.814465408805031"
## [1] "Accuracy for fold 5 : 0.844339622641509"
## [1] "Accuracy for fold 6 : 0.860062893081761"
```

```
## [1] "Accuracy for fold 7 : 0.841194968553459"
## [1] "Accuracy for fold 8 : 0.828616352201258"
## [1] "Accuracy for fold 9 : 0.844339622641509"
## [1] "Accuracy for fold 10 : 0.808176100628931"

print(paste(" Average Accuracy for Over Sampled Random Forest :", mean(accuracy.vect.os))
)

## [1] " Average Accuracy for Over Sampled Random Forest : 0.839150943396226"
```

Accuracy for Random Forest through Cross-Validation, with Over Sampled Data: 83.92%

Important Variables for Random Forest with Over Sampled Data

```
osrfImportant <- importance(OS.tuned.RandForest, type = 2)

osRFImportance <- data.frame(Variables = row.names(osrfImportant),
            Importance = round(osrfImportant[ ,'MeanDecreaseGini'],2))

osRFImportance <- osRFImportance[order((osRFImportance$Importance),decreasing = TRUE), ]

head(osRFImportance, 20)

##                                                   Variables Importance
## AgeYrs                                               AgeYrs        232
## CE_CSAT                                             CE_CSAT        211
## Estimatedcost                                 Estimatedcost        183
## CE_VALUEFORMONEY                           CE_VALUEFORMONEY        168
## BedCategory                                     BedCategory        152
## LengthofStay                                   LengthofStay        144
## Department                                       Department        136
## InsPayorcategory                           InsPayorcategory         96
## AD_TARRIFFPACKAGESEXPLAINATION AD_TARRIFFPACKAGESEXPLAINATION         91
## DP_DISCHARGETIME                           DP_DISCHARGETIME         90
## CE_ACCESSIBILITY                           CE_ACCESSIBILITY         80
## AE_ATTENDEEFOOD                             AE_ATTENDEEFOOD         76
## DP_DISCHARGEPROCESS                     DP_DISCHARGEPROCESS         68
## DP_DISCHARGEQUERIES                     DP_DISCHARGEQUERIES         62
## FNB_FOODQUALITY                             FNB_FOODQUALITY         62
## FNB_FOODDELIVERYTIME                   FNB_FOODDELIVERYTIME         53
## STATEZONE                                         STATEZONE         47
## AD_TIME                                             AD_TIME         46
## INR_ROOMAMBIENCE                           INR_ROOMAMBIENCE         43
## Sex                                                     Sex         43
```

Ada Boost with SMOTE data:

```
Adatrain.smote <- SMOTE.balanced %>% select(-CE_NPS)
Adatest.smote <- binaryTest %>% select(-CE_NPS)

Ada.smote <- rbind(Adatrain.smote,Adatest.smote)

#Converting categorical variables into dummy numerica variables

Ada.smote_nums <- dplyr::select_if(Ada.smote, is.numeric)
Ada.smote_cat <- dplyr::select_if(Ada.smote, is.factor)
```

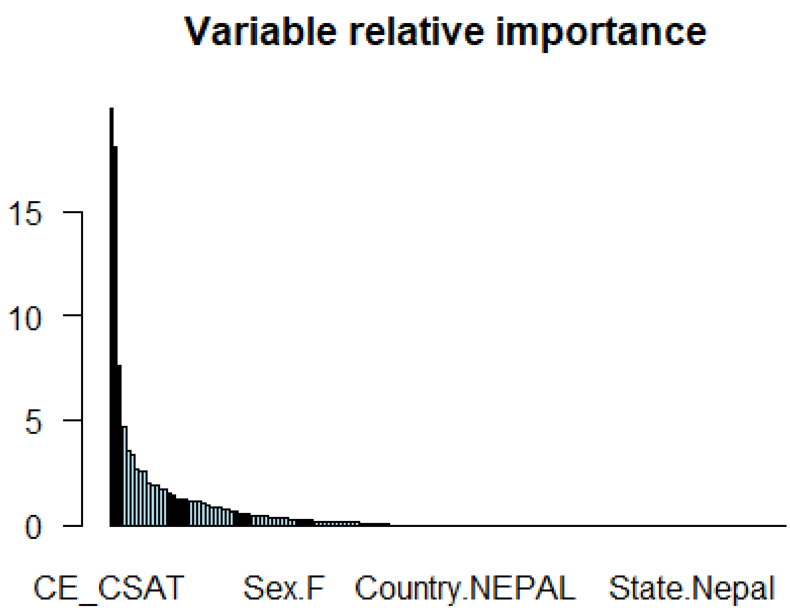
```r
var_onehot <- c('MaritalStatus','Sex','BedCategory','Department', "InsPayorcategory", "St
ate", "Country", "STATEZONE")

# One Hot Encoding

dummys1 <- dummyVars(" ~ .", data = Ada.smote_cat[,var_onehot])
dummy_cats1 <- data.frame(predict(dummys1, newdata = Ada.smote_cat[,var_onehot]))
 new.Ada.smote <- cbind(Ada.smote_nums,dummy_cats1,Ada.smote_cat$NPS_Status)
names(new.Ada.smote)[names(new.Ada.smote) =="Ada.smote_cat$NPS_Status"] <- "NPS_Status"
Adatrain.smote <- new.Ada.smote[1:6841,]
Adatest.smote <- new.Ada.smote[6842:7205,]
Ada.smote <- rbind(Adatrain.smote,Adatest.smote)

set.seed(111)
library(adabag)

k3 = 10

x = floor(nrow(Ada.smote)/k3)
accuracy.Ada.smote = rep(NA,k3)

for (i in 1:k3) {

  p1 = ((i-1) * x+1)
  p2 = (i*x)
  subset = p1:p2

  smoteAdacv.train = Ada.smote[-subset,]
  smoteAdacv.test = Ada.smote[subset,]

 smote.tuned.Ada <- boosting(NPS_Status ~ ., data = smoteAdacv.train, mfinal = 20, contro
l = rpart.control(maxdepth = 30, cp=0.005 ))

smote.predboosting <- as.factor(predict.boosting(smote.tuned.Ada,
                                      newdata = smoteAdacv.test)$class)
#length(multi.predboosting)
#length(multiAdaTest$NPS_Status)

accuracy.Ada.smote[i] <- (confusionMatrix(smote.predboosting, smoteAdacv.test$NPS_Status)
)$overall[1]

 print(paste("Accuracy for fold", i, ":", accuracy.Ada.smote[i]))

    }

## [1] "Accuracy for fold 1 : 0.802777777777778"
## [1] "Accuracy for fold 2 : 0.793055555555556"
## [1] "Accuracy for fold 3 : 0.783333333333333"
## [1] "Accuracy for fold 4 : 0.823611111111111"
## [1] "Accuracy for fold 5 : 0.683333333333333"
## [1] "Accuracy for fold 6 : 0.55"
## [1] "Accuracy for fold 7 : 0.604166666666667"
## [1] "Accuracy for fold 8 : 0.951388888888889"
## [1] "Accuracy for fold 9 : 0.963888888888889"
## [1] "Accuracy for fold 10 : 0.836111111111111"
```

```r
print(paste(" Average Accuracy for SMOTE Sampled Ada Boost Model :", mean(accuracy.Ada.sm
ote)))

## [1] " Average Accuracy for SMOTE Sampled Ada Boost Model : 0.779166666666667"
```

Accuracy for Ada Boost through Cross-Validation with SMOTE Data: 77.91%

Important Variables for Ada Boost with SMOTE Data

```r
importanceplot(smote.tuned.Ada)
```




```r
smoteadaImportant <- smote.tuned.Ada$importance

head(sort(smoteadaImportant, decreasing = TRUE),20)

##                  CE_CSAT                CE_VALUEFORMONEY
##                     19.9                            18.1
##             LengthofStay                          AgeYrs
##                      7.6                             4.8
##         AD_STAFFATTITUDE                CE_ACCESSIBILITY
##                      3.6                             3.4
##            Estimatedcost AD_TARRIFFPACKAGESEXPLAINATION
##                      2.7                             2.6
##          FNB_FOODQUALITY             INR_ROOMCLEANLINESS
##                      2.5                             2.0
##         DP_DISCHARGETIME                INR_ROOMAMBIENCE
##                      1.9                             1.9
##      DP_DISCHARGEQUERIES                   FNB_DIETICIAN
##                      1.7                             1.7
##        INR_ROOMEQUIPMENT                AE_ATTENDEECARE
##                      1.5                             1.4
##      DP_DISCHARGEPROCESS           NS_NURSEPROACTIVENESS
##                      1.2                             1.2
##     AE_PATIENTSTATUSINFO                      DOC_VISITS
##                      1.2                             1.1
```

Ada Boost with under sampled data:

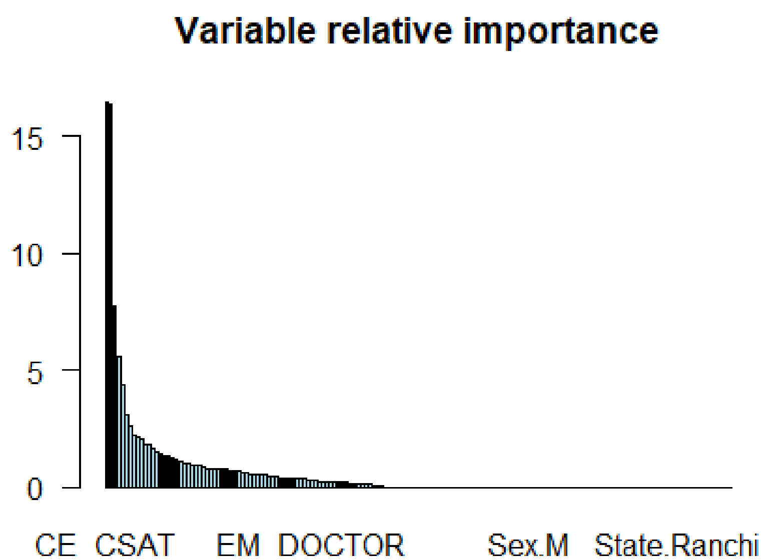
```
Adatrain.us <- underSample %>% select(-CE_NPS)
Adatest.us <- binaryTest %>% select(-CE_NPS)

Ada.us <- rbind(Adatrain.us,Adatest.us)

#Converting categorical variables into dummy numerica variables
Ada.us_nums <- dplyr::select_if(Ada.us, is.numeric)
Ada.us_cat <- dplyr::select_if(Ada.us, is.factor)

var_onehot <- c('MaritalStatus','Sex','BedCategory','Department', "InsPayorcategory", "St
ate", "Country", "STATEZONE")

# One Hot Encoding
dummys2 <- dummyVars(" ~ .", data = Ada.us_cat[,var_onehot])
dummy_cats2 <- data.frame(predict(dummys2, newdata = Ada.us_cat[,var_onehot]))
 new.Ada.us <- cbind(Ada.us_nums,dummy_cats2,Ada.us_cat$NPS_Status)
names(new.Ada.us)[names(new.Ada.us) =="Ada.us_cat$NPS_Status"] <- "NPS_Status"
Adatrain.us <- new.Ada.us[1:4000,]
Adatest.us <- new.Ada.us[4001:4364,]
Ada.us <- rbind(Adatrain.us,Adatest.us)

library(adabag)

k3 = 10

y = floor(nrow(Ada.us)/k3)
accuracy.Ada.us = rep(NA,k3)

for (i in 1:k3) {

  p3 = ((i-1) * y+1)
  p4 = (i*y)
  subset = p3:p4

  USAdacv.train = Ada.us[-subset,]
  USAdacv.test = Ada.us[subset,]


 US.tuned.Ada <- boosting(NPS_Status ~ ., data = USAdacv.train, mfinal = 20, control = rp
art.control(maxdepth = 30, cp=0.005 ))

US.predboosting <- as.factor(predict.boosting(US.tuned.Ada,
                                       newdata = USAdacv.test)$class)
#length(multi.predboosting)
#length(multiAdaTest$NPS_Status)

accuracy.Ada.us[i] <- (confusionMatrix(US.predboosting, USAdacv.test$NPS_Status))$overall
[1]

 print(paste("Accuracy for fold", i, ":", accuracy.Ada.us[i]))

    }

## [1] "Accuracy for fold 1 : 0.76605504587156"
```

```
## [1] "Accuracy for fold 2 : 0.729357798165138"
## [1] "Accuracy for fold 3 : 0.731651376146789"
## [1] "Accuracy for fold 4 : 0.731651376146789"
## [1] "Accuracy for fold 5 : 0.740825688073395"
## [1] "Accuracy for fold 6 : 0.564220183486238"
## [1] "Accuracy for fold 7 : 0.594036697247706"
## [1] "Accuracy for fold 8 : 0.594036697247706"
## [1] "Accuracy for fold 9 : 0.642201834862385"
## [1] "Accuracy for fold 10 : 0.715596330275229"
print(paste(" Average Accuracy for Under Sampled Ada Boosted model :", mean(accuracy.Ada.
us)))

## [1] " Average Accuracy for Under Sampled Ada Boosted model : 0.680963302752294"
```

Accuracy for Ada Boost through Cross-Validation with Under Sampled Data: 68.09%

Important Variables for Ada Boost with Under Sampled Data

```
importanceplot(US.tuned.Ada)
```




```
usadaImportant <- US.tuned.Ada$importance

head(sort(usadaImportant, decreasing = TRUE),20)

##                      CE_CSAT                CE_VALUEFORMONEY
##                         16.4                            16.4
##                       AgeYrs                   Estimatedcost
##                          7.7                             5.6
##                 LengthofStay                CE_ACCESSIBILITY
##                          4.4                             3.1
##              FNB_FOODQUALITY AD_TARRIFFPACKAGESEXPLAINATION
##                          2.6                             2.2
##          FNB_FOODDELIVERYTIME                DP_DISCHARGETIME
##                          2.1                             2.1
##              AE_ATTENDEEFOOD                           Sex.F
##                          1.8                             1.8
##          AE_PATIENTSTATUSINFO      OVS_OVERALLSTAFFPROMPTNESS
##                          1.7                             1.5
##                FNB_DIETICIAN              BedCategory.GENERAL
```

```
##                      1.4                          1.3
##       DP_DISCHARGEQUERIES          NS_NURSEPROACTIVENESS
##                      1.3                          1.3
##          INR_ROOMAMBIENCE                   DOC_VISITS
##                      1.1                          1.1
```

Ada Boost with Over Sample data:

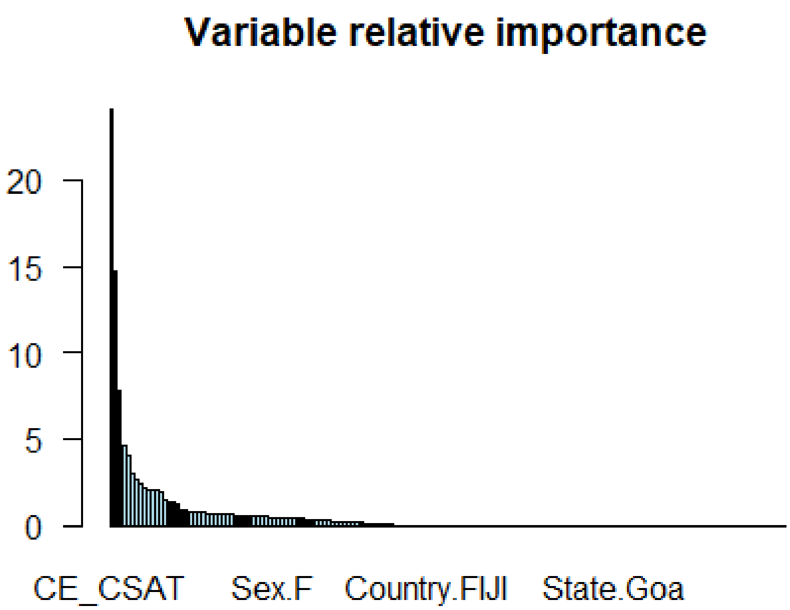
```
Adatrain.os <- overSample %>% select(-CE_NPS)
Adatest.os <- binaryTest %>% select(-CE_NPS)

Ada.os <- rbind(Adatrain.os,Adatest.os)

#Converting categorical variables into dummy numerica variables
Ada.os_nums <- dplyr::select_if(Ada.os, is.numeric)
Ada.os_cat <- dplyr::select_if(Ada.os, is.factor)

var_onehot <- c('MaritalStatus','Sex','BedCategory','Department', "InsPayorcategory", "St
ate", "Country", "STATEZONE")

# One Hot Encoding
dummys3 <- dummyVars(" ~ .", data = Ada.smote_cat[,var_onehot])
dummy_cats3 <- data.frame(predict(dummys3, newdata = Ada.os_cat[,var_onehot]))
 new.os.smote <- cbind(Ada.os_nums,dummy_cats3,Ada.os_cat$NPS_Status)
names(new.os.smote)[names(new.os.smote) =="Ada.os_cat$NPS_Status"] <- "NPS_Status"
Adatrain.os <- new.os.smote[1:6000,]
Adatest.os <- new.os.smote[6001:6364,]
Ada.os <- rbind(Adatrain.os,Adatest.os)

library(adabag)

k3 = 10

z = floor(nrow(Ada.os)/k3)
accuracy.Ada.os = rep(NA,k3)

for (i in 1:k3) {

  p5 = ((i-1) * z+1)
  p6 = (i*z)
  subset = p5:p6

  OSAdacv.train = Ada.os[-subset,]
  OSAdacv.test = Ada.os[subset,]

 OS.tuned.Ada <- boosting(NPS_Status ~ ., data = OSAdacv.train, mfinal = 20, control = rp
art.control(maxdepth = 30, cp=0.005 ))

OS.predboosting <- as.factor(predict.boosting(OS.tuned.Ada,
                                      newdata = OSAdacv.test)$class)
#levels(OS.predboosting)
#length(multiAdaTest$NPS_Status)

accuracy.Ada.os[i] <- (confusionMatrix(OS.predboosting, OSAdacv.test$NPS_Status)$overall)
[1]
```

```
 print(paste("Accuracy for fold", i, ":", accuracy.Ada.os[i]))

    }

## [1] "Accuracy for fold 1 : 0.764150943396226"
## [1] "Accuracy for fold 2 : 0.754716981132076"
## [1] "Accuracy for fold 3 : 0.754716981132076"
## [1] "Accuracy for fold 4 : 0.726415094339623"
## [1] "Accuracy for fold 5 : 0.773584905660377"
## [1] "Accuracy for fold 6 : 0.64622641509434"
## [1] "Accuracy for fold 7 : 0.660377358490566"
## [1] "Accuracy for fold 8 : 0.627358490566038"
## [1] "Accuracy for fold 9 : 0.638364779874214"
## [1] "Accuracy for fold 10 : 0.712264150943396"
print(paste(" Average Accuracy for Over Sampled Ada Boost Model :", mean(accuracy.Ada.os)
))

## [1] " Average Accuracy for Over Sampled Ada Boost Model : 0.705817610062893"
```

Accuracy for Ada Boost through Cross-Validation with Over Sampled Data: 70.58%

Important Variables for Ada Boost with Over Sampled Data

```
importanceplot(OS.tuned.Ada)
```




```
osadaImportant <- OS.tuned.Ada$importance

head(sort(osadaImportant, decreasing = TRUE),20)

##                        CE_CSAT                 CE_VALUEFORMONEY
##                          24.07                            14.70
##                         AgeYrs                    Estimatedcost
##                           7.84                             4.64
##               CE_ACCESSIBILITY                   FNB_FOODQUALITY
##                           4.08                             3.03
##               INR_ROOMAMBIENCE                   AE_ATTENDEEFOOD
##                           2.61                             2.46
```

```
##            BedCategory.GENERAL            FNB_FOODDELIVERYTIME
##                           2.14                            2.09
## AD_TARRIFFPACKAGESEXPLAINATION                    LengthofStay
##                           2.07                            2.01
##            DP_DISCHARGEQUERIES             INR_ROOMCLEANLINESS
##                           1.89                            1.42
##               DP_DISCHARGETIME                AD_STAFFATTITUDE
##                           1.41                            1.37
##                     DOC_VISITS      DOC_TREATMENTEFFECTIVENESS
##                           1.25                            0.91
##                        AD_TIME                NS_NURSEPATIENCE
##                           0.88                            0.77
```

9. What should be the strategy for using the model to improve patient experience in the hospital and reduce proportion of detractors?

Summarizing all Models:

Logistic Regression – Full Model	Logistic Regression – Stepwise Model	Random Forest – Multi Class	Ada-Boost Multi Class	Random Forest Binary Class	Ada-Boost Binary Class
Test Data Accuracy = 90.1%	**Test Data Accuracy = 90.7%**	**Cross Validation Accuracy = 72.09% Test Data Accuracy = 68.7%**	**Training Data Accuracy = 73.7% Test Data Accuracy = 67.8**	**Cross Validation Accuracy = 77.02% Test Data Accuracy = 73.9%**	**Training Data Accuracy = 80.5% Test Data Accuracy = 71.7**
48 variables used, may lead to over-fitting	**16 variables used, with same accuracy.**				

SMOTE, Under Sampling & Over Sampling Results:

	SMOTE – Random Forest	SMOTE – Ada-Boost	Under Sampling – Random Forest	Under Sampling – Ada-Boost	Over Sampling – Random Forest	Over Sampling – Ada-Boost
CV Accuracy	84.34%	**77.91%**	**70.92%**	**68.09%**	**83.92**	**70.58%**

Objective of Manipal Health Enterprises: Reduce the proportion of Detractors.

Strategy: The constructed models help in finding out the reasons why a customer is a Detractor. The important variables identified in the models are the ones that lead to a customer becoming Promotor or Detractor. Manipal Health Enterprises can use these findings to develop a strategy that addresses those problem areas and reduce the proportion of Detractors.

To detect whether a customer is Detractor or not, and why is he/she a Detractor, Manipal Health can use Binary Class Classification.

Logistic Regression gives a good accuracy of 90.1%, with the following 16 variables:

AgeYrs + Sex + Department + CE_ACCESSIBILITY + CE_VALUEFORMONEY + EM_NURSING + AD_TIME + AD_TARRIFFPACKAGESEXPLAINATION + INR_ROOMCLEANLINESS + FNB_FOODDELIVERYTIME + DOC_VISITS + NS_NURSEPROACTIVENESS + OVS_SECURITYATTITUDE + DP_DISCHARGETIME + DP_DISCHARGEQUERIES + DP_DISCHARGEPROCESS

Both Ensemble methods, Random Forest and Ada-Boost provide similar results, with a Training accuracy in the range of 77-80% and Test Accuracy in the range of 71-74%.

Random Forest does a bit better on Unseen data, with an accuracy of 73.9%.

On applying SMOTE and Over Sampling, on Random Forest the results are improved quite a bit, with a 10-Fold Cross Validation average accuracy of 84.34% & 83.92% respectively

The important variables identified from all the models are quite similar.
From Random Forest with SMOTE data, important variables are:

CE_CSAT *- Overall, were you Satisfied by the service you recieved*
CE_VALUEFORMONEY *– Did you receive overall value for money?*
AgeYrs
Estimatedcost
DP_DISCHARGETIME – *Time Taken for Discharge Process*
BedCategory
CE_ACCESSIBILITY – *Did you find us when you need us?*
Department
DP_DISCHARGEPROCESS - *Overall Discharge Process*
AE_ATTENDEEFOOD – *Food options for your Attendee*
AD_TARRIFFPACKAGESEXPLAINATION – Explanation of Tarrif & Packages available
InsPayorcategory
DP_DISCHARGEQUERIES – *Communication & handling of queries*
FNB_FOODQUALITY – *Overall Quality & Taste of Food*
AD_TIME – *Time Taken for Admission*
STATEZONE
FNB_FOODDELIVERYTIME – *Timliness of Service*
INR_ROOMPEACE- *Peace & Quite in the Room*
FNB_DIETICIAN – *Regular Diet Counselling*

From the above, we understand that Value for Money, Overall Satisfaction, Food Quality, Timliness of Services, time taken for Dischare process, explanation of tarrif packages, peace & quite in Room, are major contributors for the given NPS Score. Thus, MHE should maintain these features in order to reduce the proportion of Detractors.