CIMP_GP_2503

March 31, 2022

1 Setup

[1]:
```
rm(list = ls())
options(scipen=999)
set.seed(10)

# Packages for Data Manipulation
library("dplyr")
library('tidyverse')
library("data.table")

# Stuff for Graphs and Plots
library("ggplot2")
library("ggpubr")
library("gplots")
library("plotly")
library("ggrepel")
library("RColorBrewer")


##I define a personalized theme for ggplot based on a default theme
mytheme<-theme_minimal()+theme(plot.title = element_text(hjust = 0.5))

# General Tools for Regressions and Marginal Effects
library("car")
library("margins")

# Package for regression uplifting models
library("tools4uplift")

# Package for XGBoosting
library('xgboost')

# Package for HCF
library("grf")

# Miscellaneous
```

```r
library("matrixStats")
library("reshape2")
library("Rcpp")
library('mltools')
library('glmnet')
library('caret')
library("mlr")


#Automatically Install Missing Packages
listOfPackages <- c("dplyr","tidyverse","data.table","ggplot2","ggpubr",
                    "gplots","plotly","ggrepel","RColorBrewer",
                    "reshape2","margins",␣
 ↪"tools4uplift","xgboost","grf","ggplot2","matrixStats",
                    "Rcpp","car","mltools","glmnet",
                    "caret","mlr")
for (i in listOfPackages){
     if(! i %in% installed.packages()){
         install.packages(i, dependencies = TRUE)
         library(i)
     }
}
```

```
Attaching package: 'dplyr'


The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union


Warning message:
"package 'tidyverse' was built under R version 4.0.5"
-- Attaching packages
--------------------------------------------------------------------------------
tidyverse 1.3.1 --

v ggplot2 3.3.3     v purrr   0.3.4
v tibble  3.0.6     v stringr 1.4.0
v tidyr   1.1.3     v forcats 0.5.1
v readr   1.4.0
```

```
Warning message:
"package 'tidyr' was built under R version 4.0.5"
-- Conflicts ------------------------------------------------------
------------------------- tidyverse_conflicts() --
x dplyr::filter()  masks stats::filter()
x purrr::flatten() masks
jsonlite::flatten()
x dplyr::lag()     masks stats::lag()


Attaching package: 'data.table'


The following object is masked from 'package:purrr':

    transpose


The following objects are masked from 'package:dplyr':

    between, first, last


Warning message:
"package 'gplots' was built under R version 4.0.5"

Attaching package: 'gplots'


The following object is masked from 'package:stats':

    lowess


Warning message:
"package 'plotly' was built under R version 4.0.5"

Attaching package: 'plotly'


The following object is masked from 'package:ggplot2':

    last_plot


The following object is masked from 'package:stats':
```

```
    filter


The following object is masked from 'package:graphics':

    layout


Loading required package: carData


Attaching package: 'car'


The following object is masked from 'package:purrr':

    some


The following object is masked from 'package:dplyr':

    recode


Warning message:
"package 'margins' was built under R version 4.0.5"
Warning message:
"package 'tools4uplift' was built under R version 4.0.5"
Warning message:
"package 'xgboost' was built under R version 4.0.5"

Attaching package: 'xgboost'


The following object is masked from 'package:plotly':

    slice


The following object is masked from 'package:dplyr':

    slice


Warning message:
"package 'grf' was built under R version 4.0.5"

Attaching package: 'matrixStats'
```

```
The following object is masked from 'package:dplyr':

    count



Attaching package: 'reshape2'


The following objects are masked from 'package:data.table':

    dcast, melt


The following object is masked from 'package:tidyr':

    smiths


Warning message:
"package 'Rcpp' was built under R version 4.0.5"
Warning message:
"package 'mltools' was built under R version 4.0.5"

Attaching package: 'mltools'


The following object is masked from 'package:tidyr':

    replace_na


Warning message:
"package 'glmnet' was built under R version 4.0.5"
Loading required package: Matrix


Attaching package: 'Matrix'


The following objects are masked from 'package:tidyr':

    expand, pack, unpack


Loaded glmnet 4.1-3
```

```
Warning message:
"package 'caret' was built under R version 4.0.5"
Loading required package: lattice


Attaching package: 'caret'


The following object is masked from 'package:purrr':

    lift


Warning message:
"package 'mlr' was built under R version 4.0.5"
Loading required package: ParamHelpers

Warning message:
"package 'ParamHelpers' was built under R version 4.0.5"
Warning message: 'mlr' is in 'maintenance-only' mode since July 2019.
Future development will only happen in 'mlr3'
(<https://mlr3.mlr-org.com>). Due to the focus on 'mlr3' there might be
uncaught bugs meanwhile in {mlr} - please consider switching.


Attaching package: 'mlr'


The following object is masked from 'package:caret':

    train
```

2 Data Generation

[2]:

```
# total number of users under study - Increased from 1000 to 100000 (experiment)
num_users <- 100000

u_id <- seq(1,num_users)

u_age <- sample(c(1,2,3,4,5,6),num_users,replace=T,prob=c(0.1,0.30,0.35,0.15,0.
↪05,0.05))
# 1=<18 2=[18,25) 3=[25,35) 4=[35,45), 5=[45,55), 6=>55

u_gender <- sample(c(1,2),num_users,replace=T,prob=c(0.6,0.4))
```

```r
# 1=M, 2=F

u_weekly_utilisation <- sample(0:7,num_users,replace=T)
# number of days using the service in a week

u_sub_utilisation <- round(runif(num_users,0,1),2)
# proportion of time spent on the service since the first subscription

#u_rating_given <- sample(0:5,num_users,replace=T)
u_rating_given<-round(runif(num_users,0,5),2)

# rating on a scale from 0 to 5 given by each user to the platform

u_format_pref <- sample(c(1,2,3),num_users,replace=T,prob=c(0.5,0.4,0.1))
# 1=TV-series, 2=movies, 3=documentaries

u_genre_pref <- sample(1:7,num_users,replace=T)
# 1=action, 2=comedy, 3=romance, 4=sci-fi, 5=animation, 6=drama, 7=horror

u_other_sub <- sample(0:1,num_users,replace=T)
# binary variable where 0=not subscribed to other streaming platforms, 1=yes

# creating the data table with all the users
USERS <- data.table(u_id, u_gender, u_age, u_weekly_utilisation,
 ↪u_sub_utilisation, u_format_pref,
                    u_genre_pref, u_rating_given, u_other_sub)
```

[3]:

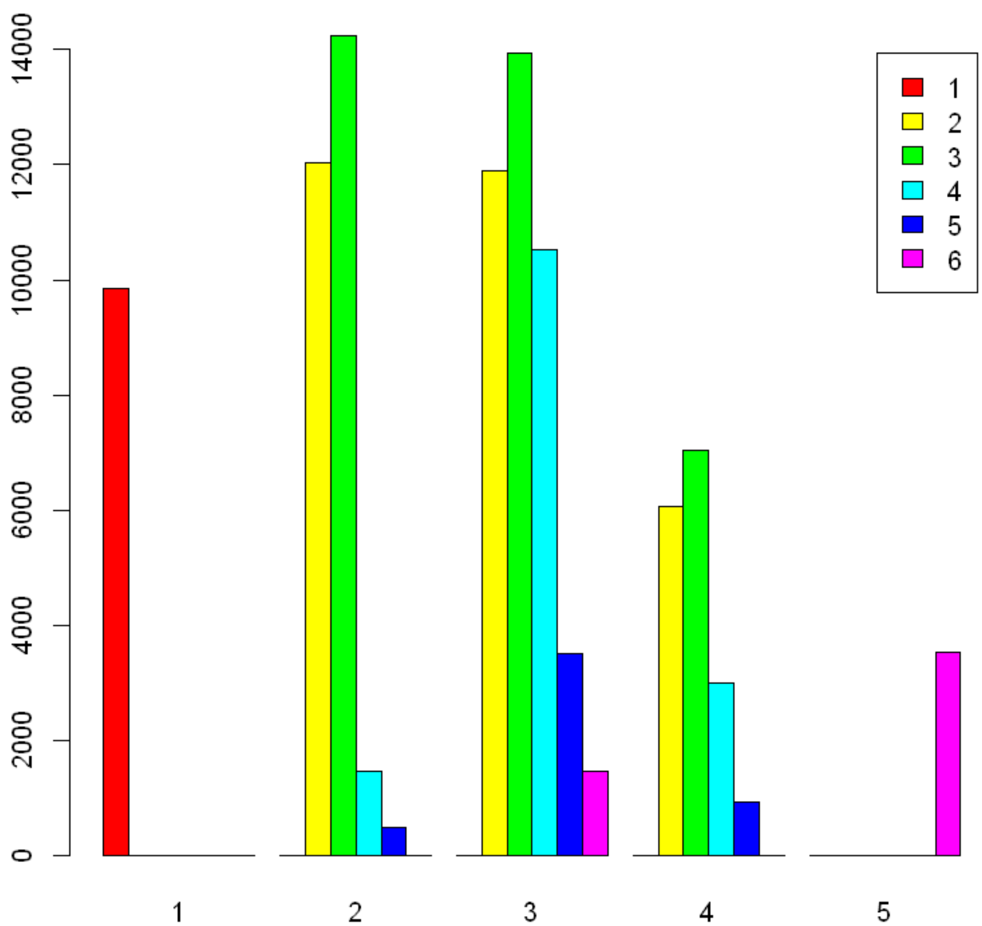
```r
USERS
```

A data.table: 100000 × 9

u_id	u_gender	u_age	u_weekly_utilisation	u_sub_utilisation	u_format_
<int>	<dbl>	<dbl>	<int>	<dbl>	<dbl>
1	2	2	2	0.40	1
2	2	3	1	0.38	1
3	2	2	6	0.31	2
4	1	4	6	0.09	2
5	2	3	0	0.33	1
6	2	3	7	0.06	1
7	1	3	6	0.82	2
8	1	3	6	0.16	1
9	2	2	1	0.84	1
10	2	2	1	0.55	1
11	1	4	5	0.24	1
12	2	2	3	0.69	1
13	1	3	4	0.73	1
14	1	2	3	0.93	1
15	1	2	4	0.05	1
16	1	2	6	0.62	2
17	1	3	0	0.52	2
18	2	3	3	0.91	1
19	2	2	6	0.90	2
20	2	1	3	0.45	1
21	1	1	2	0.92	2
22	2	2	3	0.29	3
23	1	4	5	0.81	1
24	2	2	0	0.26	1
25	2	2	3	0.15	3
26	1	4	6	0.11	2
27	1	1	0	0.09	2
28	1	3	5	0.64	2
29	1	4	7	0.96	1
30	1	2	1	0.49	2
...	...	...	...	...	...
99971	2	3	1	0.16	1
99972	1	3	7	0.16	1
99973	2	6	0	0.23	3
99974	2	2	2	0.55	2
99975	2	3	7	0.80	1
99976	1	4	0	0.32	1
99977	2	3	2	0.32	2
99978	2	2	5	0.93	3
99979	1	1	3	0.45	1
99980	1	4	7	0.93	3
99981	2	4	1	0.36	2
99982	1	2	1	0.10	1
99983	2	1	3	0.29	1
99984	2	3	6	0.42	3
99985	1	3	2	0.21	1
99986	1	2	7	0.05	2
99987	1	4	0	0.43	1
99988	1	3	3	0.05	1
99989	1	2	7	0.89	2
99990	2	3	6	0.41	1

```
[4]: # defining the users' occupation variable based on some conditions
USERS$u_occupation[u_age==1] <- 1
USERS$u_occupation[u_age==2|u_age==3] <-
 ↪sample(c(2,3,4),nrow(USERS[u_age==2|u_age==3]),replace=T,prob=c(0.4,0.4,0.2))
USERS$u_occupation[u_age==4|u_age==5] <-
 ↪sample(c(2,3,4),nrow(USERS[u_age==4|u_age==5]),replace=T,prob=c(0.1,0.7,0.2))
USERS$u_occupation[u_age==6] <-
 ↪sample(c(3,5),nrow(USERS[u_age==6]),replace=T,prob=c(0.3,0.7))
# occupation: 1=student 2=part-time 3=full-time 4=unemployed 5=retired
# age: 1=<18 2=[18,25) 3=[25,35) 4=[35,45), 5=[45,55), 6=>55

table(USERS$u_age, USERS$u_occupation)
barplot(table(USERS$u_age, USERS$u_occupation), beside=T, legend=T,
 ↪col=rainbow(6))
```

	1	2	3	4	5
1	9850	0	0	0	0
2	0	12037	11894	6068	0
3	0	14243	13944	7039	0
4	0	1465	10517	3005	0
5	0	482	3511	940	0
6	0	0	1470	0	3535

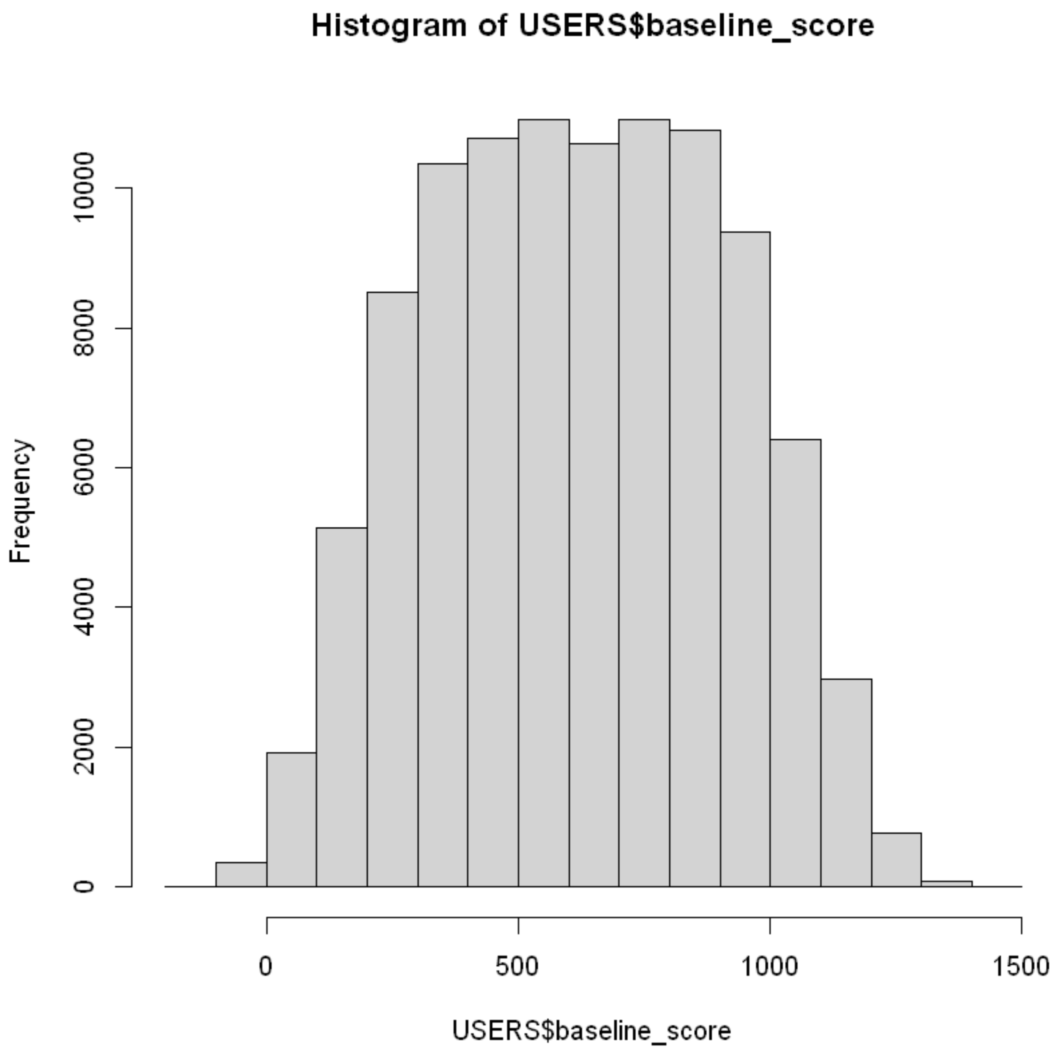


[5]:
```
# we suppose that our streaming service is focused on action and sci-fi␣
↪tv-series
# u_genre_pref(1=action||4=sci-fi), u_format_pref(1=series), u_age(-),␣
↪u_occupation(-)
# u_other_sub(-), u_rating_given(+), u_sub_utilisation(+),␣
↪u_weekly_utilisation(+)
# add error term from rnorm
```

[6]:
```
# score = u_genre_pref(1|4) 80 + u_format_pref(1) 100 + u_age(1|2) 30 -␣
↪u_age(3|4|5|6) 30
#         + u_occupation(1|4|5) 30 - u_occupation(2|3) 30 - u_other_sub*55 +␣
↪u_rating_given*50
```

```r
#         + u_sub_utilisation*130 + u_weekly_utilisation*115 + error
# NB: coefficients arbitrarly given
# USERS[,score:
 ↪=u_rating_given*50+u_sub_utilisation*130+u_weekly_utilisation*115-u_other_sub*55+rnorm(1)*1

# Deterministic Portion of Utility
USERS[,baseline_score:
 ↪=u_rating_given*50+u_sub_utilisation*130+u_weekly_utilisation*115-u_other_sub*55]
USERS[u_genre_pref==1|u_genre_pref==4, baseline_score:=baseline_score+80]
USERS[u_format_pref==1, baseline_score:=baseline_score+100]
USERS[,baseline_score:
 ↪=ifelse(u_age==1|u_age==2,baseline_score+30,baseline_score-30)]
USERS[,baseline_score:
 ↪=ifelse(u_occupation==2|u_occupation==3,baseline_score-30,baseline_score+30)]

summary(USERS$baseline_score)
hist(USERS$baseline_score)
```

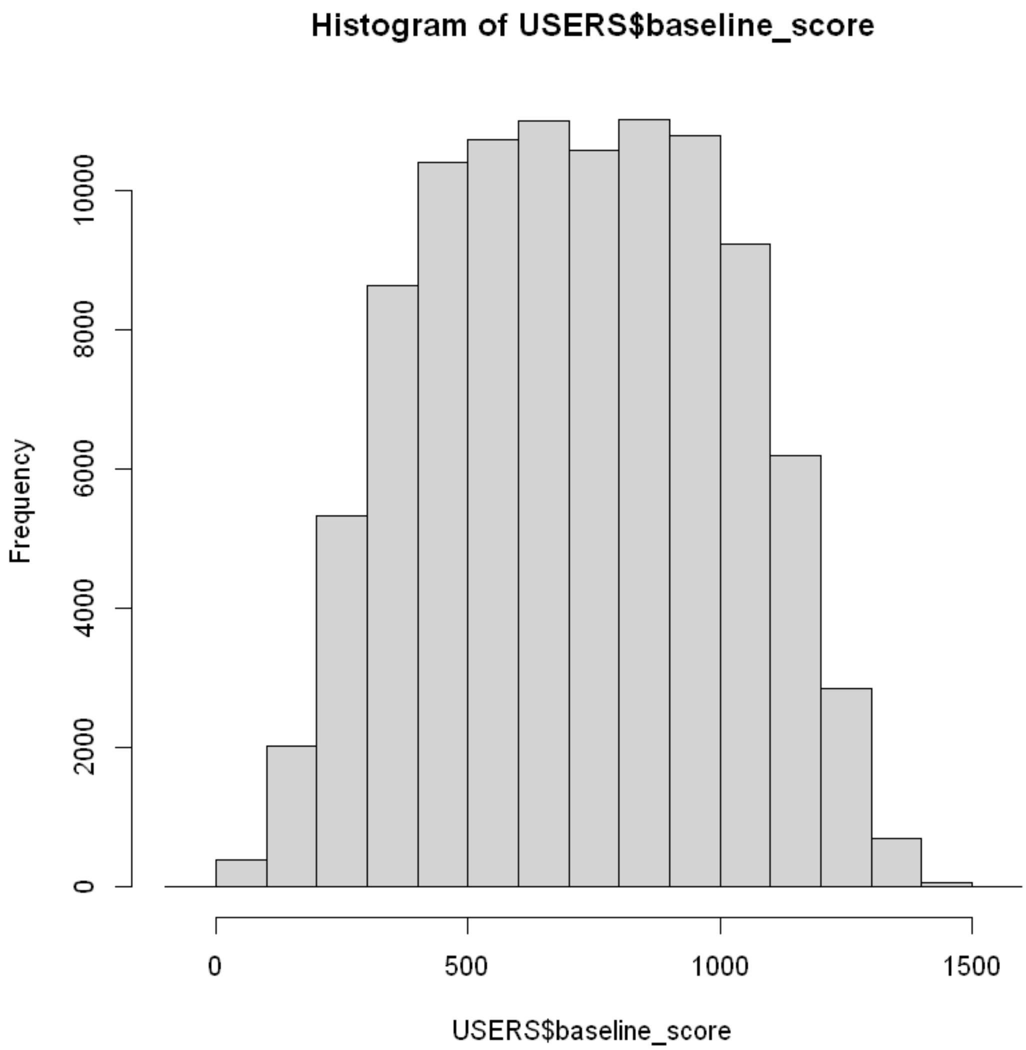
```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
-107.5   389.1   618.5   619.3   849.8  1417.2 
```



[7]:

```
# Random Component of Utility (observable to customers but unobservable to the
 ↪econometrician)
USERS$baseline_score=USERS$baseline_score+rnorm(1,0,70)

# NOTE: Remember to set appropriate size for the noise

summary(USERS$baseline_score)
hist(USERS$baseline_score)
```

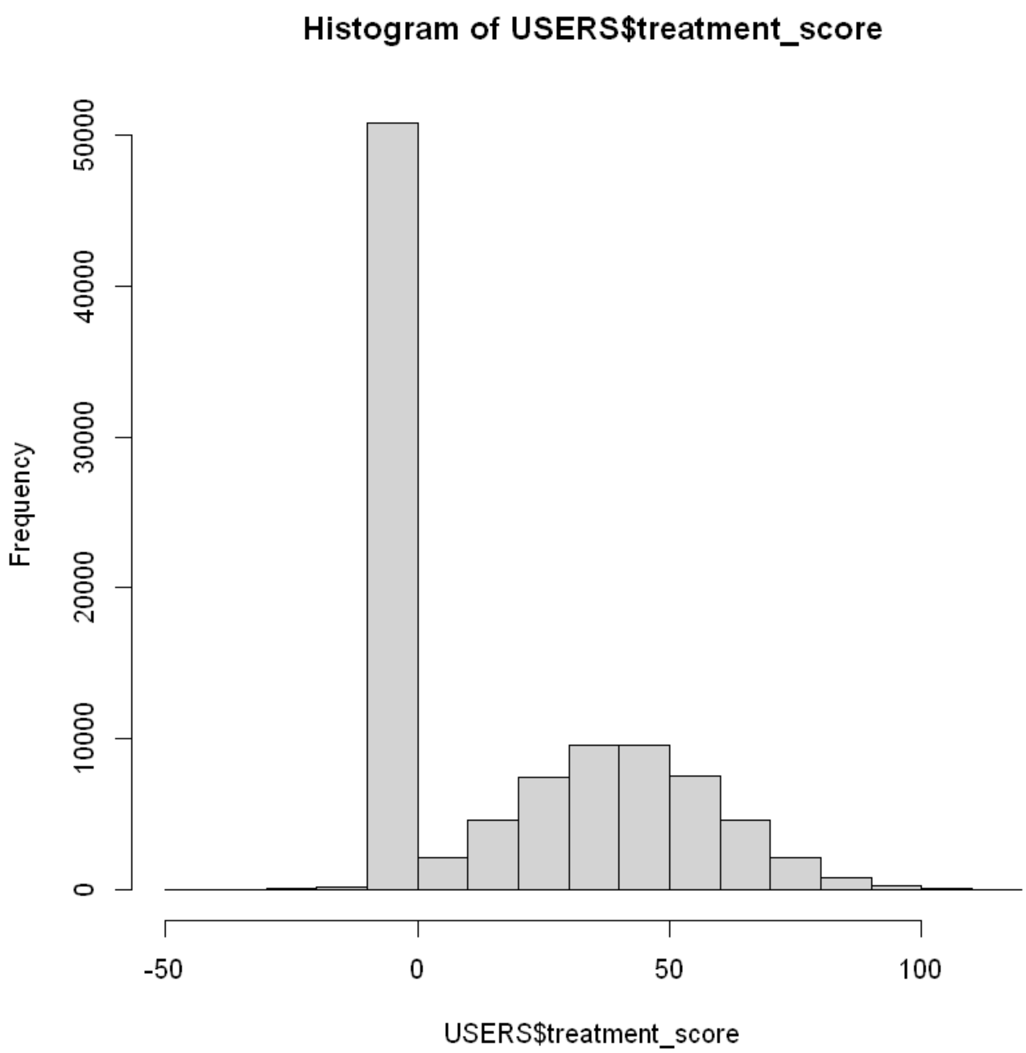
```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-12.31  484.29  713.69  714.45  944.99 1512.39
```



[8]:
```
# Creating Treatment Effects

# treatment variable randomly assigned to the users
USERS$treated <- sample(0:1,num_users,replace=T)

# The impact of our policy can be divided into two components:
# First: an additive component independent of covariates and positive on average
USERS[,treatment_score:=ifelse(treated==1,rnorm(num_users,40,20),0)]
summary(USERS$treatment_score)
hist(USERS$treatment_score)
# NOTE: Remember to set appropriate size for the random component
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

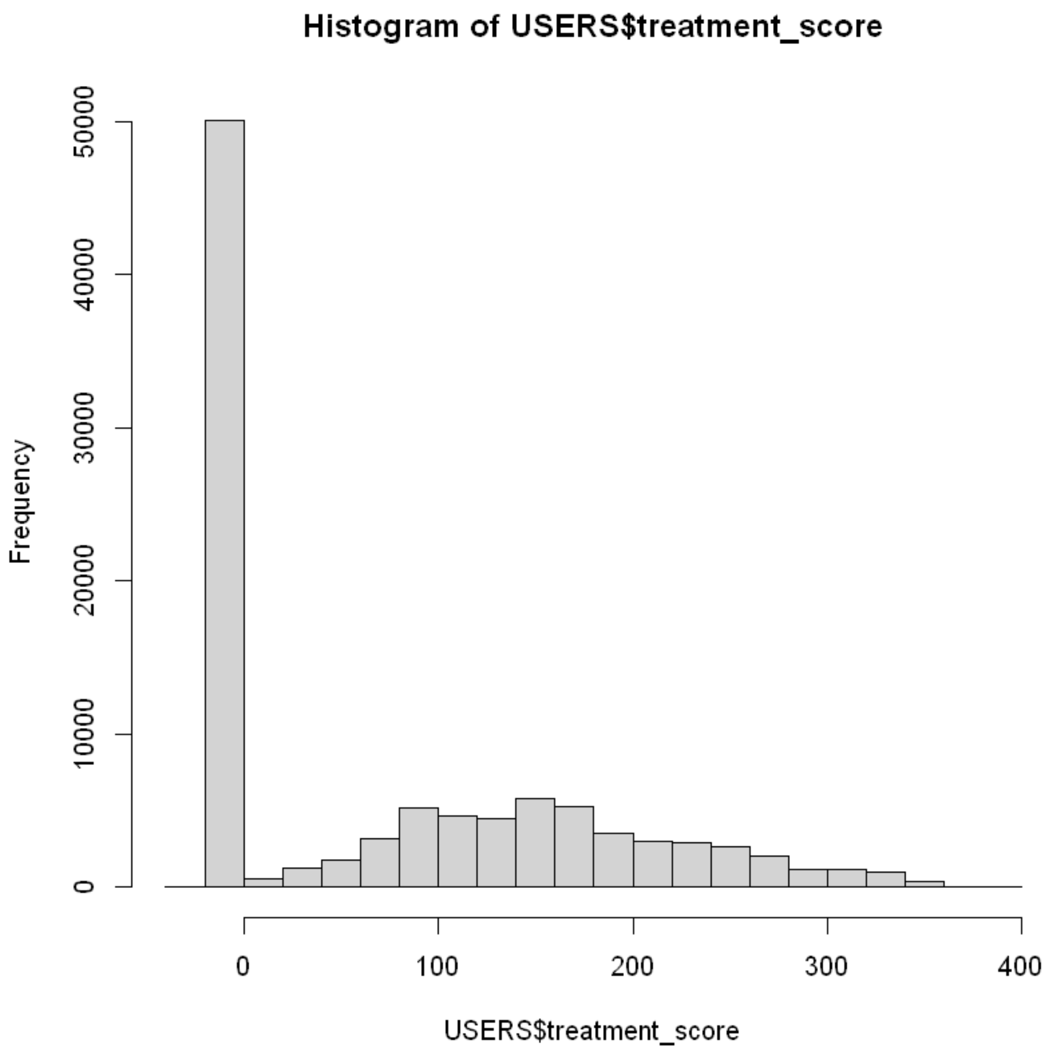
```
-43.28     0.00     0.00    20.04    40.10   119.16
```




```
[9]: # Second: part of the effect depends on some user's characteristics
      ↪(interactions).
     # For example, #to capture the higher price sensitivity of young people and
      ↪students/unemployed:
     USERS[treated==1,treatment_score:
      ↪=ifelse(u_age==1|u_age==2,treatment_score+70,treatment_score)]
     USERS[treated==1,treatment_score:
      ↪=ifelse(u_occupation==2|u_occupation==3|u_occupation==5,treatment_score,treatment_score+100
     # We may assume we face different degrees of competition depending on the
      ↪favorite genre of users:
```

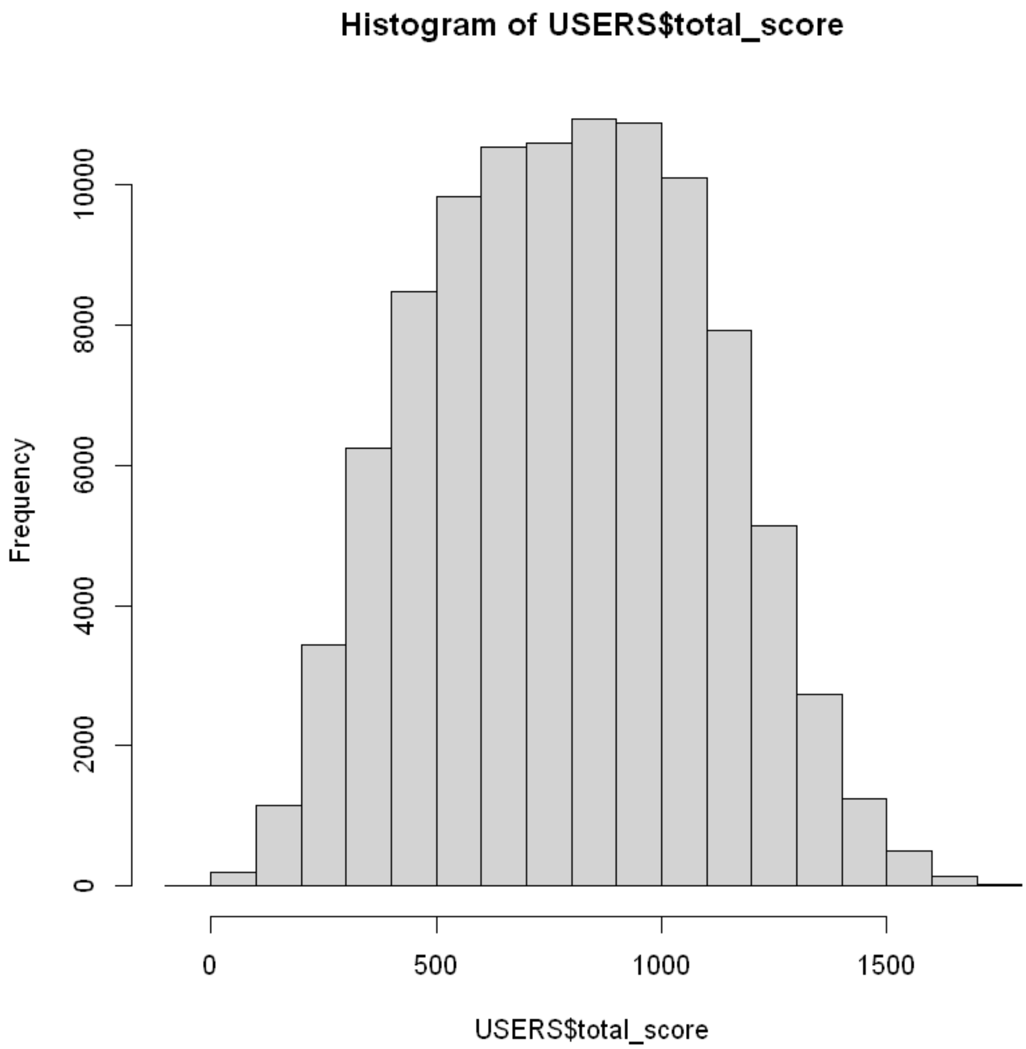
```
USERS[treated==1,treatment_score:
 ↪=ifelse(u_genre_pref==2|u_genre_pref==3,treatment_score,treatment_score+50)]
# Finally, a voucher would reduce multihoming costs of being subscribed to␣
 ↪multiple platforms
USERS[u_other_sub==1&treated==1, treatment_score:=treatment_score+60]

# Overall, we get
summary(USERS$treatment_score)
hist(USERS$treatment_score)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -28.22    0.00    0.00   80.23  153.44  393.40
```



[10]:
```
# Unifying baseline and treatment  scores
USERS$total_score=USERS$baseline_score+USERS$treatment_score
summary(USERS$total_score)
hist(USERS$total_score)
```

```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-12.31  556.79  795.89  794.68 1026.27 1796.81
```



[11]:
```
#How to assign churn?
#Assume that 15% of customer churn
threshold_churn=quantile(USERS$baseline_score, prob=c(.15))
USERS[,resub:=ifelse(total_score>threshold_churn,1,0)]
```

```
summary(USERS$resub)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.0000  1.0000  1.0000  0.9003  1.0000  1.0000 
```

[12]:
```
USERS
```

A data.table: 100000 × 15

u_id	u_gender	u_age	u_weekly_utilisation	u_sub_utilisation	u_format_
<int>	<dbl>	<dbl>	<int>	<dbl>	<dbl>
1	2	2	2	0.40	1
2	2	3	1	0.38	1
3	2	2	6	0.31	2
4	1	4	6	0.09	2
5	2	3	0	0.33	1
6	2	3	7	0.06	1
7	1	3	6	0.82	2
8	1	3	6	0.16	1
9	2	2	1	0.84	1
10	2	2	1	0.55	1
11	1	4	5	0.24	1
12	2	2	3	0.69	1
13	1	3	4	0.73	1
14	1	2	3	0.93	1
15	1	2	4	0.05	1
16	1	2	6	0.62	2
17	1	3	0	0.52	2
18	2	3	3	0.91	1
19	2	2	6	0.90	2
20	2	1	3	0.45	1
21	1	1	2	0.92	2
22	2	2	3	0.29	3
23	1	4	5	0.81	1
24	2	2	0	0.26	1
25	2	2	3	0.15	3
26	1	4	6	0.11	2
27	1	1	0	0.09	2
28	1	3	5	0.64	2
29	1	4	7	0.96	1
30	1	2	1	0.49	2
...	...	...	...	...	...
99971	2	3	1	0.16	1
99972	1	3	7	0.16	1
99973	2	6	0	0.23	3
99974	2	2	2	0.55	2
99975	2	3	7	0.80	1
99976	1	4	0	0.32	1
99977	2	3	2	0.32	2
99978	2	2	5	0.93	3
99979	1	1	3	0.45	1
99980	1	4	7	0.93	3
99981	2	4	1	0.36	2
99982	1	2	1	0.10	1
99983	2	1	3	0.29	1
99984	2	3	6	0.42	3
99985	1	3	2	0.21	1
99986	1	2	7	0.05	2
99987	1	4	0	0.43	1
99988	1	3	3	0.05	1
99989	1	2	7	0.89	2
99990	2	3	6	0.41	1

[13]:
```
# Adding additional noise by allowing an erratic behavior of 5% of customer
set.seed(10)
perc_err=num_users*0.05
USERS[sample(USERS$u_id,perc_err),resub:=ifelse(resub==0,1,0)]

USERS
```

A data.table: 100000 × 15

u_id	u_gender	u_age	u_weekly_utilisation	u_sub_utilisation	u_format_
<int>	<dbl>	<dbl>	<int>	<dbl>	<dbl>
1	2	2	2	0.40	1
2	2	3	1	0.38	1
3	2	2	6	0.31	2
4	1	4	6	0.09	2
5	2	3	0	0.33	1
6	2	3	7	0.06	1
7	1	3	6	0.82	2
8	1	3	6	0.16	1
9	2	2	1	0.84	1
10	2	2	1	0.55	1
11	1	4	5	0.24	1
12	2	2	3	0.69	1
13	1	3	4	0.73	1
14	1	2	3	0.93	1
15	1	2	4	0.05	1
16	1	2	6	0.62	2
17	1	3	0	0.52	2
18	2	3	3	0.91	1
19	2	2	6	0.90	2
20	2	1	3	0.45	1
21	1	1	2	0.92	2
22	2	2	3	0.29	3
23	1	4	5	0.81	1
24	2	2	0	0.26	1
25	2	2	3	0.15	3
26	1	4	6	0.11	2
27	1	1	0	0.09	2
28	1	3	5	0.64	2
29	1	4	7	0.96	1
30	1	2	1	0.49	2
...	...	...	...	...	...
99971	2	3	1	0.16	1
99972	1	3	7	0.16	1
99973	2	6	0	0.23	3
99974	2	2	2	0.55	2
99975	2	3	7	0.80	1
99976	1	4	0	0.32	1
99977	2	3	2	0.32	2
99978	2	2	5	0.93	3
99979	1	1	3	0.45	1
99980	1	4	7	0.93	3
99981	2	4	1	0.36	2
99982	1	2	1	0.10	1
99983	2	1	3	0.29	1
99984	2	3	6	0.42	3
99985	1	3	2	0.21	1
99986	1	2	7	0.05	2
99987	1	4	0	0.43	1
99988	1	3	3	0.05	1
99989	1	2	7	0.89	2
99990	2	3	6	0.41	1

[14]:
```
# Scaling scores
# USERS$score_scaled <- scale(USERS$score)  #scaling the scores
# USERS[,churn:=ifelse(score>0,0,1)] #if positive score, the user doesn't churn␣
↪(0), otherwise they churn (1)
# to create some error in the dataset, for some random ids switch btw 0 and 1
# seed(10)
# USERS[sample(USERS$u_id,100),churn:=ifelse(churn==1,0,1)]
```

[15]:
```
data = USERS %>% select(-baseline_score, -treatment_score, -total_score) %>%␣
↪rename(y=resub, treat=treated)
data=as.data.frame(data)
```

[16]:
```
# Converting categorical variables into factors
data = data %>%
  mutate_at(vars(u_gender, u_format_pref, u_genre_pref, u_other_sub,␣
↪u_occupation),
            funs(factor))

# We also perform one hot encoding, to be used in models which do not support␣
↪factors

data_cat= data %>% select(u_gender, u_format_pref, u_genre_pref, u_other_sub,␣
↪u_occupation)
data_noncat= data %>% select(-u_gender, -u_format_pref, -u_genre_pref,␣
↪-u_other_sub, -u_occupation, -u_id)
data_oh = one_hot(as.data.table(data_cat))
data_oh=cbind(data$u_id, data_oh, data_noncat)
colnames(data_oh)[1]='u_id'
data_oh$y=as.factor(data_oh$y)
```

```
Warning message:
"`funs()` was deprecated in dplyr 0.8.0.
Please use a list of either functions or lambdas:

  # Simple named list:
  list(mean = mean, median = median)

  # Auto named with `tibble::lst()`:
  tibble::lst(mean, median)

  # Using lambdas
  list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
This warning is displayed once every 8 hours.
Call `lifecycle::last_warnings()` to see where this warning was

generated."
```

[17]:
```
# Dividing our Dataset in Three parts: Training, Test and Holdout

#holdout_data_id = sample(seq_len(nrow(data)), size = num_users*0.20)
#working_data = data[-holdout_data_id, ]
#holdout_data = data[holdout_data_id, ]
#split = SplitUplift(holdout_data, 0.6, c("treat", "y"))
set.seed(10)
split = SplitUplift(data, 0.6, c("treat", "y"))
train=split[[1]]
test=split[[2]]

# Reproducing the sample split on the hot encoded dataset
set.seed(10)
split_oh = SplitUplift(data_oh, 0.6, c("treat", "y"))
train_oh=as.data.frame(split_oh[[1]])
test_oh=as.data.frame(split_oh[[2]])

# Define the set of covariates (without y and treat)
features=colnames(train)[2:(length(colnames(train))-2)]
features_oh=colnames(train_oh)[2:(length(colnames(train_oh))-2)]
```

3 Exploratory Data Analysis

- Exploring the distributions of our features
- Look at the differences in treatment effects across various “univariete” subgroups (for example ages, occupation) in order to have a preliminary idea of the extent of possible heterogenity.
- Look at the correlation matrix

4 Traditional A/B Testing

In questa sezione potremmo sviluppare l’analisi dei risultati del semplice A/B test, per identificare l’Average Treatment Effect.

5 Uplift Models

5.1 Two-Models

5.1.1 Intuition

[18]:
```
# First of all, we create a copy of data,train and test set exclusively for␣
↪two-models
data_tm=data
train_tm=train
test_tm=test

#We then separate treated and control in both groups
```

```
train_tm_control=subset(train_tm, treat==0)
train_tm_treatment=subset(train_tm, treat==1)
test_tm_control = subset(test_tm, treat==0)
test_tm_treatment = subset(test_tm, treat==1)

# Intuition
# logit_model_C<-glm(y ~ u_weekly_utilisation + u_rating_given + u_gender,␣
↪family= binomial(link=logit), data=train_tm_control)
# logit_model_T<-glm(y ~ u_weekly_utilisation + u_rating_given + u_gender,␣
↪family= binomial(link=logit),  data=train_tm_treatment)
# data_tm$pred_C= logit_model_C %>% predict(data_tm, type = "response")
# data_tm$pred_T= logit_model_T %>% predict(data_tm, type = "response")
# data_tm$tau=data_tm$pred_T-data_tm$pred_C
# print('Estimated Probabilities when Customers are not treated')
# plot_ly(x=data_tm$u_weekly_utilisation, y=data_tm$u_rating_given,␣
↪z=data_tm$pred_C,  type="scatter3d", mode="markers")
# print('Estimated Probabilities when Customers are treated')
# plot_ly(x=data_tm$u_weekly_utilisation, y=data_tm$u_rating_given,␣
↪z=data_tm$pred_T,  type="scatter3d", mode="markers")
# print('Estimated TE computed as the difference between the abovementioned␣
↪probs')
# plot_ly(x=data_tm$u_weekly_utilisation, y=data_tm$u_rating_given,␣
↪z=data_tm$tau,  type="scatter3d", mode="markers")
```

5.1.2 Two-Model: Logit

[19]:
```
# Defining the formula for the model
logitformula=as.formula(paste("y~", paste(features, collapse="+")))

logit_model_C<-glm(logitformula, family= binomial(link=logit),␣
↪data=train_tm_control)
logit_model_T<-glm(logitformula, family= binomial(link=logit),␣
↪data=train_tm_treatment)



# Computing the propability of resub for individuals on both the
# the train and the test set

train_tm$pred_C= logit_model_C %>% predict(train_tm, type = "response")
train_tm$pred_T= logit_model_T %>% predict(train_tm, type = "response")

#computing the difference between these probabilities (tau): it is the␣
↪estimated individual treatment effect
train_tm$tau= train_tm$pred_T - train_tm$pred_C
```

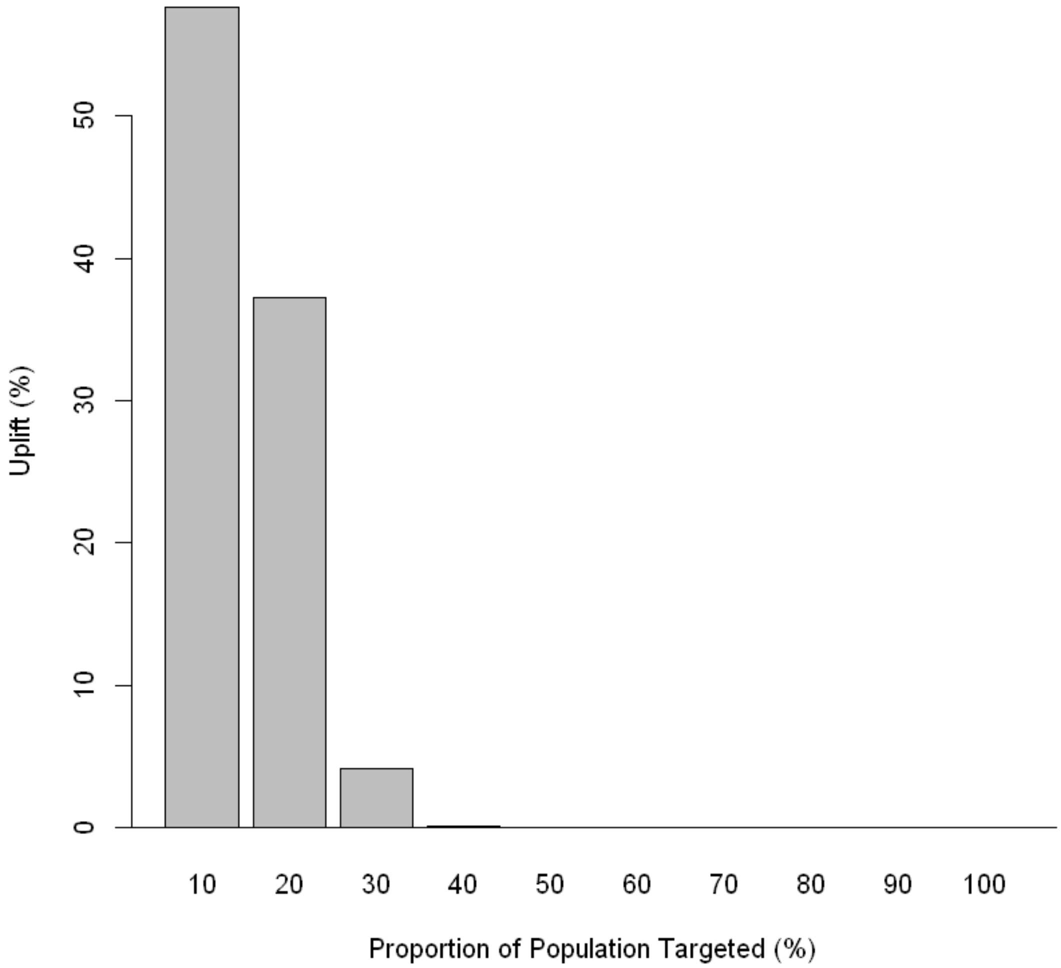
```
test_tm$pred_C= logit_model_C %>% predict(test_tm, type = "response")
test_tm$pred_T= logit_model_T %>% predict(test_tm, type = "response")
test_tm$tau= test_tm$pred_T - test_tm$pred_C
```

[20]:
```
# Model Evaluation on the test set

perf_tm=PerformanceUplift(data = test_tm, treat = "treat",
                          outcome = "y", prediction = "tau", equal.intervals =␣
 ↪TRUE, nb.group = 10)

perf_tm
barplot.PerformanceUplift(perf_tm)

QiniArea(perf_tm)
```

```
      Targeted Population (%) Incremental Uplift (%) Observed Uplift (%)
 [1,]                     0.1               6.126173         57.65277950
 [2,]                     0.2               9.669139         37.24125619
 [3,]                     0.3              10.036062          4.09055920
 [4,]                     0.4              10.128185          0.05068424
 [5,]                     0.5              10.111556          0.00000000
 [6,]                     0.6              10.164670          0.00000000
 [7,]                     0.7              10.045130          0.00000000
 [8,]                     0.8              10.064818          0.00000000
 [9,]                     0.9              10.038281          0.00000000
[10,]                     1.0               9.986970          0.00000000
attr(,"class")
[1] "print.PerformanceUplift"
```

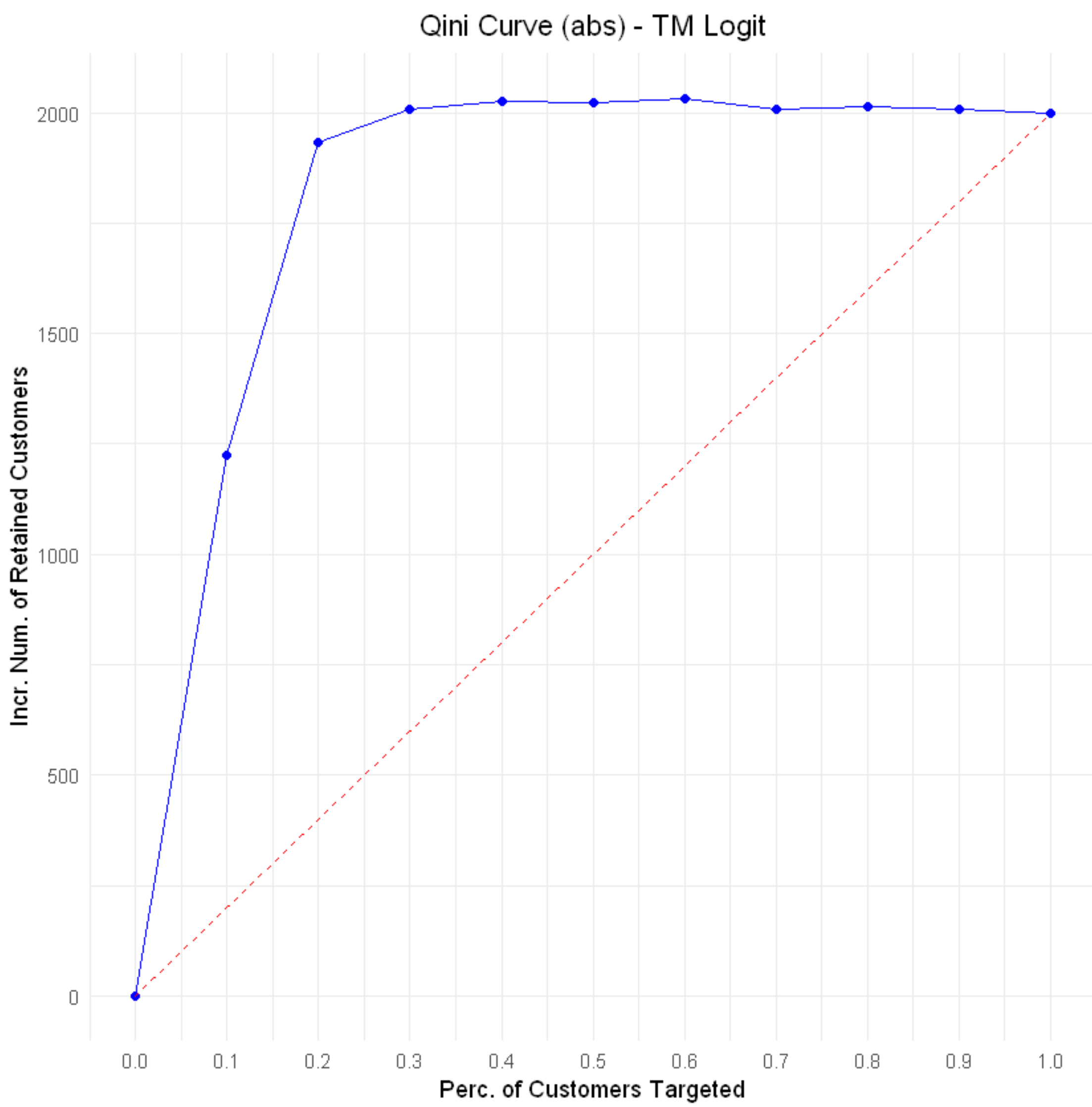
0.816496580927726

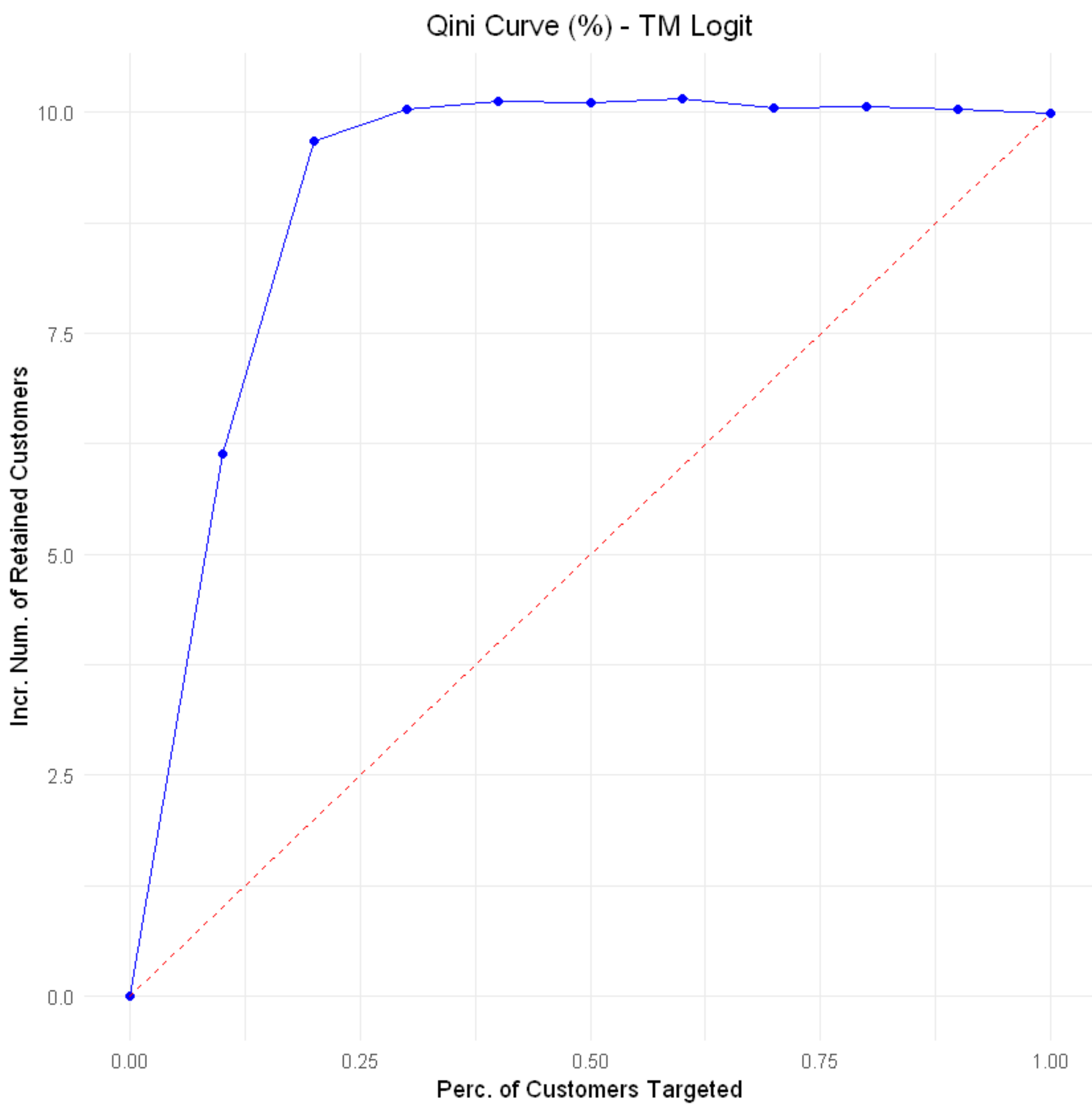
4.09966707616079



[21]:
```
# Plotting Qini curve and Qini Coeff on the test set - scrivere funzione che lo␣
↪faccia
# in automatico

df=data.frame(matrix(nrow=10, ncol=3))
df[,1]=perf_tm[[1]]
df[,2]=round(perf_tm[[6]],2)
df[,3]=round(perf_tm[[7]],2)
colnames(df)=c("Dec", "num.incr", "perc.incr")
firstrow=numeric(3)
df=rbind(firstrow,df)
```

```
##Plot Qini curves
qini_curve1<-ggplot(df, aes(x=Dec, y=num.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (abs) - TM Logit", y="Incr. Num. of Retained␣
↪Customers", x="Perc. of Customers Targeted")+
  scale_x_continuous(breaks=seq(0, 1, 0.1))+geom_segment(x = 0, y=0, xend=1,␣
↪yend=df[11,2], color="red",
                                                                    linetype="dashed",␣
↪size=0.5)
qini_curve1

qini_curve2<-ggplot(df, aes(x=Dec, y=perc.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (%) - TM Logit", y="Incr. Num. of Retained␣
↪Customers", x="Perc. of Customers Targeted")+
  xlim(0, 1)+geom_segment(x = 0, y=0, xend=1, yend=df[11,3], color="red",
                              linetype="dashed", size=0.5)
qini_curve2
```


Qini Curve (abs) - TM Logit
Incr. Num. of Retained Customers
Perc. of Customers Targeted
0
500
1000
1500
2000
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0



Improving the model through model selection

[22]:
```
#### 2.1.2 Model selection ####



# Here there are two options: implementing model selection as one would do
# for binary classification, considering model as separated and using the
# the best single models possible; or implementing model selection by
# so as to maximize the Qini area.





#Once the two models have been estimated, let's derive once gain the
```

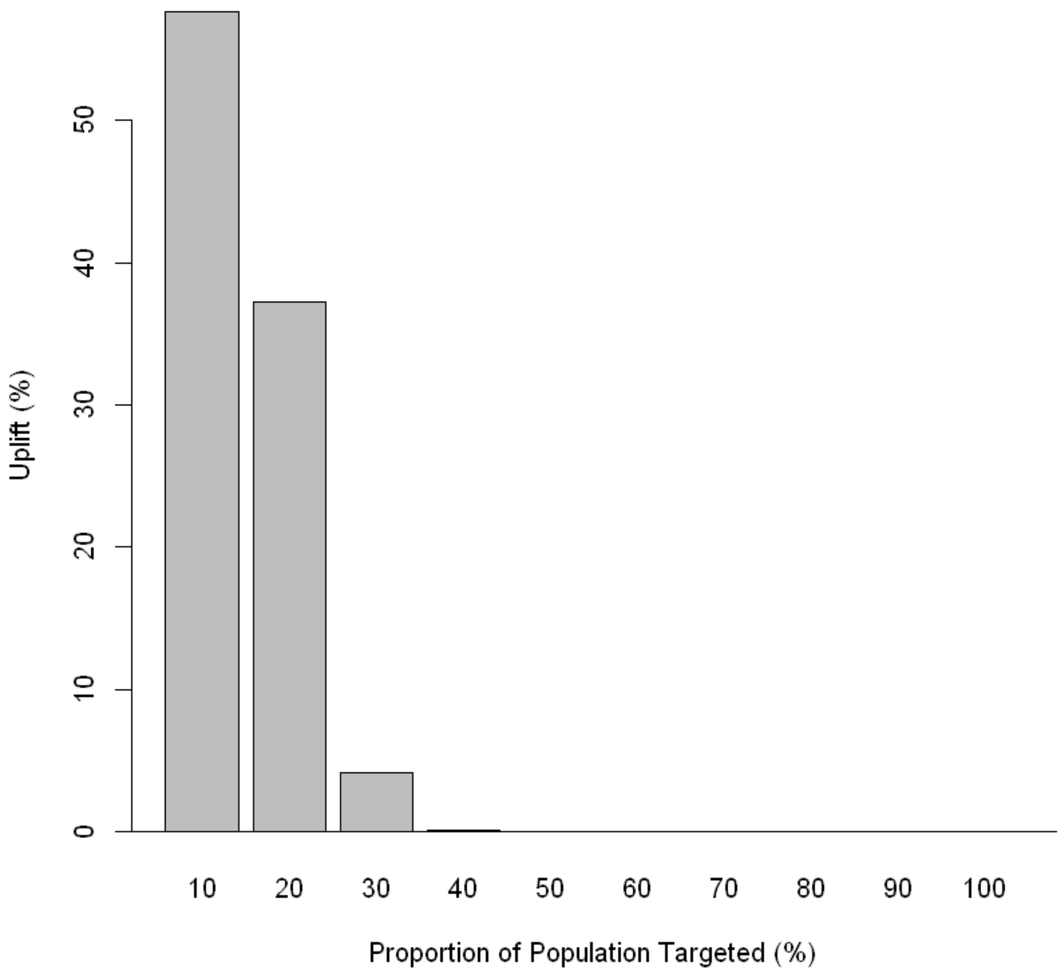
```r
# estimated treatment effects




# Evaluating Performance, Qini curve and Qini Coeff on the test set - scrivere␣
↪funzione che lo faccia
# in automatico

perf_tm_final=PerformanceUplift(data = test_tm, treat = "treat",
                                outcome = "y", prediction = "tau", equal.
↪intervals = TRUE, nb.group = 10)

perf_tm_final
barplot.PerformanceUplift(perf_tm_final)

QiniArea(perf_tm_final)

# Plotting Qini curve and Qini Coeff on the test set - scrivere funzione che lo␣
↪faccia
# in automatico

df=data.frame(matrix(nrow=10, ncol=3))
df[,1]=perf_tm_final[[1]]
df[,2]=round(perf_tm_final[[6]],2)
df[,3]=round(perf_tm_final[[7]],2)
colnames(df)=c("Dec", "num.incr", "perc.incr")
firstrow=numeric(3)
df=rbind(firstrow,df)


##Plot Qini curves
qini_curve1<-ggplot(df, aes(x=Dec, y=num.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (abs) - TM Logit (opt)", y="Incr. Num. of␣
↪Retained Customers", x="Perc. of Customers Targeted")+
  scale_x_continuous(breaks=seq(0, 1, 0.1))+geom_segment(x = 0, y=0, xend=1,␣
↪yend=df[11,2], color="red",
                                                         linetype="dashed",␣
↪size=0.5)
qini_curve1

qini_curve2<-ggplot(df, aes(x=Dec, y=perc.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (%) - TM Logit (Opt)", y="Incr. Num. of␣
↪Retained Customers", x="Perc. of Customers Targeted")+
```

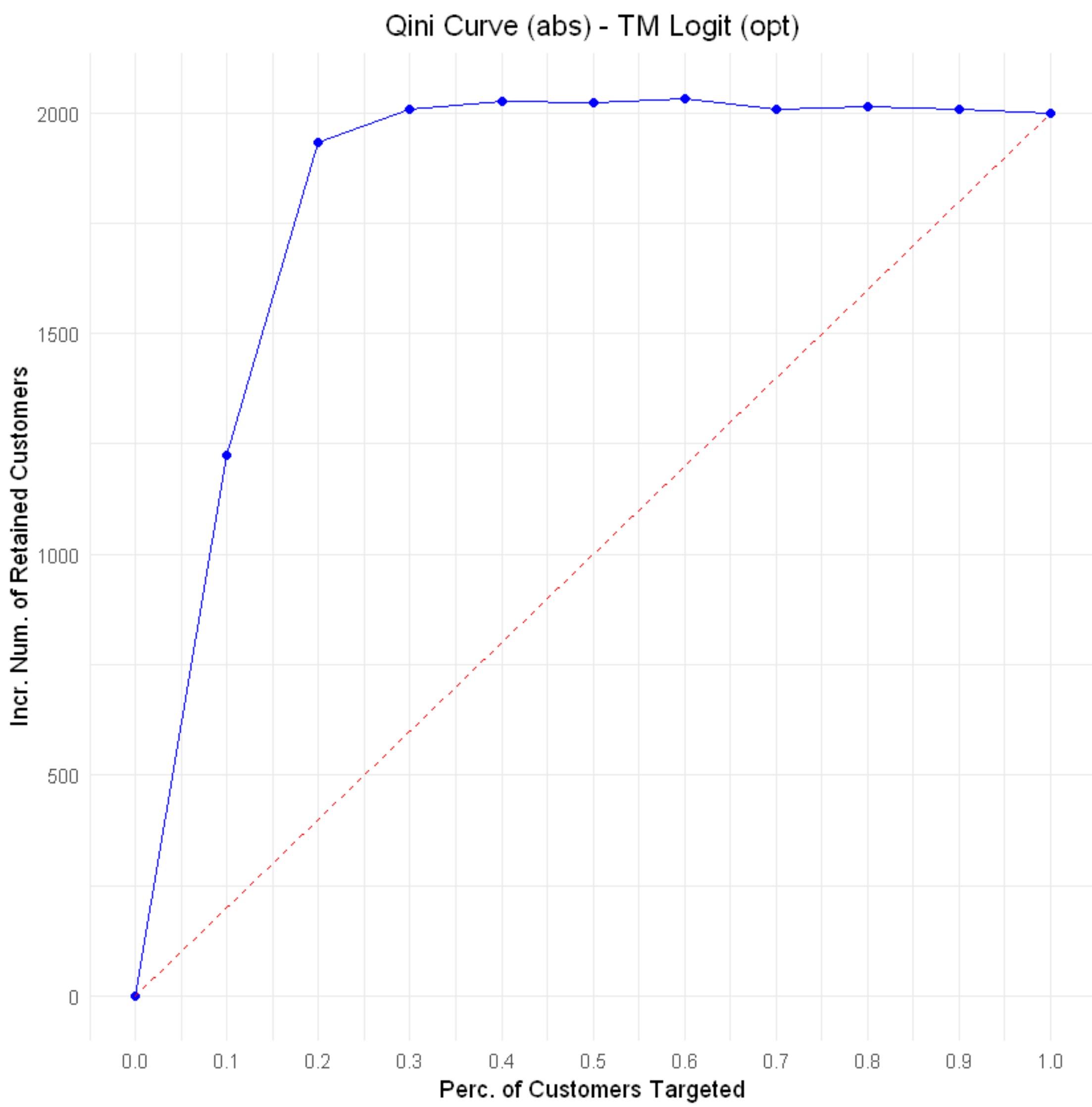
```
  xlim(0, 1)+geom_segment(x = 0, y=0, xend=1, yend=df[11,3], color="red",
                          linetype="dashed", size=0.5)
qini_curve2
```

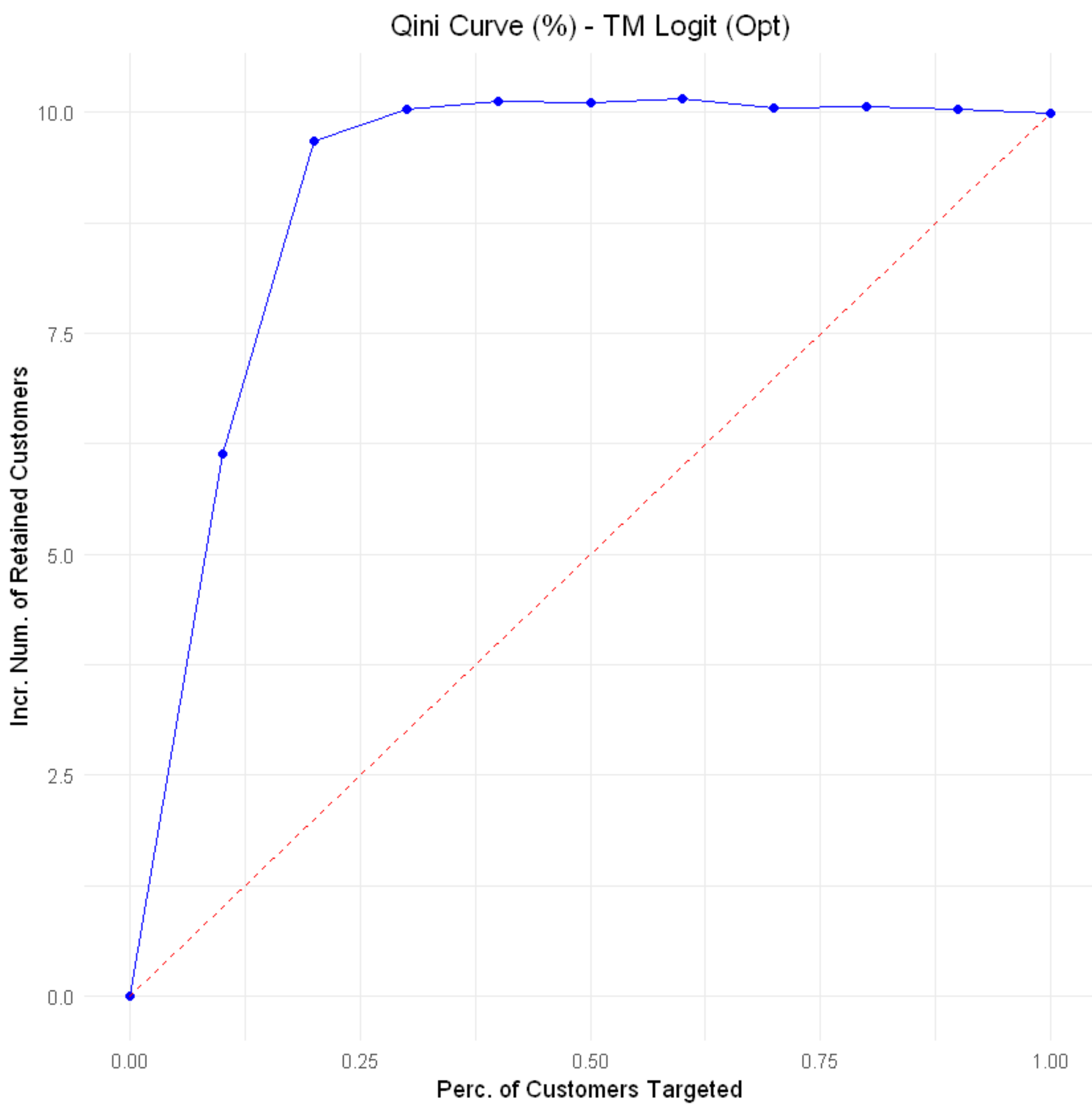
```
      Targeted Population (%) Incremental Uplift (%) Observed Uplift (%)
 [1,]                     0.1               6.126173         57.65277950
 [2,]                     0.2               9.669139         37.24125619
 [3,]                     0.3              10.036062          4.09055920
 [4,]                     0.4              10.128185          0.05068424
 [5,]                     0.5              10.111556          0.00000000
 [6,]                     0.6              10.164670          0.00000000
 [7,]                     0.7              10.045130          0.00000000
 [8,]                     0.8              10.064818          0.00000000
 [9,]                     0.9              10.038281          0.00000000
[10,]                     1.0               9.986970          0.00000000
attr(,"class")
[1] "print.PerformanceUplift"
```

0.816496580927726

4.09966707616079


Uplift (%)
0
10
20
30
40
50
10
20
30
40
50
60
70
80
90
100
Proportion of Population Targeted (%)


Qini Curve (abs) - TM Logit (opt)
2000
1500
1000
500
0
Incr. Num. of Retained Customers
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Perc. of Customers Targeted



5.1.3 XGBoost

Source: https://humboldt-wi.github.io/blog/research/applied_predictive_modeling_19/social_pressure/

[23]:
```
# Let's experiment with a more complex Classifier: XGBoost -- codice preso␣
↪online

#Setting Up the xgboost learner

xgb_learner <- makeLearner("classif.xgboost", predict.type = "prob", par.vals =␣
↪list(
  objective = "binary:logistic", eval_metric = "error"))
```

```
xgb_params <- makeParamSet(
  makeIntegerParam("nrounds", lower = 100, upper = 500),␣
↪makeIntegerParam("max_depth", lower = 1, upper = 10),
  makeNumericParam("eta", lower = .1, upper = .5), makeNumericParam("lambda",␣
↪lower = -1, upper = 0, trafo = function(x) 10^x))
ctrl <- makeTuneControlRandom(maxit = 5)  #nel codice era 15, ma per ora ho␣
↪diminuito per far prima
resample_desc <- makeResampleDesc("CV", iters = 4)


#creating the model for treatment group:
task<-makeClassifTask(data=train_oh[ ,!(colnames(train_oh) == "treat")],␣
↪target="y")
tuned_params <- tuneParams(learner = xgb_learner,task = task, resampling =␣
↪resample_desc,
                           par.set = xgb_params,control = ctrl)
treatment_xgbmodel<- mlr::train(learner = setHyperPars(learner =␣
↪xgb_learner,par.vals = tuned_params$x),task = task)

#creating the model for control group:
task<-makeClassifTask(data=test_oh[ ,!(colnames(test_oh) ==␣
↪"treat")],target="y")
tuned_params <- tuneParams(learner = xgb_learner,task = task,resampling =␣
↪resample_desc,
                           par.set = xgb_params,control = ctrl)
control_xgbmodel<- mlr::train(learner = setHyperPars(learner = xgb_learner,par.
↪vals = tuned_params$x),task = task)

#making treatment effect estimates on train and test data:
train_tm$pred_T_xgb<-predict(treatment_xgbmodel, newdata=train_oh[ ,!
↪(colnames(train_oh) == "treat")])$data[[2]]
train_tm$pred_C_xgb<-predict(control_xgbmodel, newdata=train_oh[ ,!
↪(colnames(train_oh) == "treat")])$data[[2]]
train_tm$tau_xgb<-train_tm$pred_T_xgb-train_tm$pred_C_xgb

test_tm$pred_T_xgb<-predict(treatment_xgbmodel,newdata=test_oh[ ,!
↪(colnames(test_oh) == "treat")])$data[[2]]
test_tm$pred_C_xgb<-predict(control_xgbmodel,newdata=test_oh[ ,!
↪(colnames(test_oh) == "treat")])$data[[2]]
test_tm$tau_xgb<-test_tm$pred_T_xgb-test_tm$pred_C_xgb

#Evaluating Performance

perf_xgb=PerformanceUplift(data = test_tm, treat = "treat",
```

```
                            outcome = "y", prediction = "tau_xgb", equal.
↪intervals = TRUE, nb.group = 10)

perf_xgb
barplot.PerformanceUplift(perf_xgb)

QiniArea(perf_xgb)
```

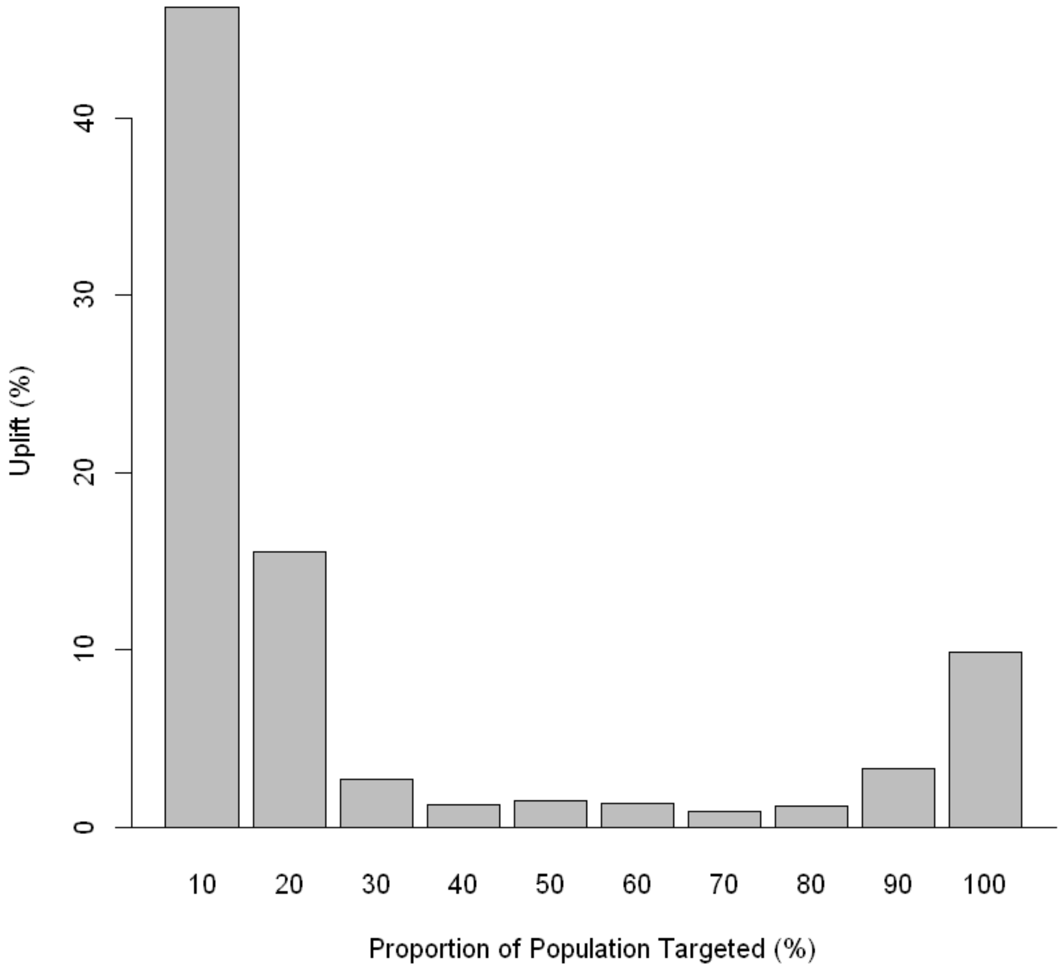
```
[Tune] Started tuning learner classif.xgboost for parameter set:

             Type len Def     Constr Req Tunable Trafo
nrounds   integer   -   - 100 to 500   -    TRUE     -
max_depth integer   -   -    1 to 10   -    TRUE     -
eta       numeric   -   - 0.1 to 0.5   -    TRUE     -
lambda    numeric   -   -    -1 to 0   -    TRUE     Y

With control class: TuneControlRandom

Imputation value: 1

[Tune-x] 1: nrounds=165; max_depth=5; eta=0.126; lambda=0.108

[Tune-y] 1: mmce.test.mean=0.1264500; time: 0.3 min

[Tune-x] 2: nrounds=135; max_depth=1; eta=0.103; lambda=0.401

[Tune-y] 2: mmce.test.mean=0.1365667; time: 0.1 min

[Tune-x] 3: nrounds=181; max_depth=4; eta=0.176; lambda=0.201

[Tune-y] 3: mmce.test.mean=0.1271500; time: 0.3 min

[Tune-x] 4: nrounds=308; max_depth=7; eta=0.236; lambda=0.115

[Tune-y] 4: mmce.test.mean=0.1312667; time: 0.8 min

[Tune-x] 5: nrounds=325; max_depth=5; eta=0.499; lambda=0.675

[Tune-y] 5: mmce.test.mean=0.1360667; time: 0.6 min

[Tune] Result: nrounds=165; max_depth=5; eta=0.126; lambda=0.108 :
mmce.test.mean=0.1264500

[Tune] Started tuning learner classif.xgboost for parameter set:

             Type len Def     Constr Req Tunable Trafo
nrounds   integer   -   - 100 to 500   -    TRUE     -
```

```
max_depth integer   -   -    1 to 10   -    TRUE     -
eta       numeric   -   - 0.1 to 0.5   -    TRUE     -
lambda    numeric   -   -    -1 to 0   -    TRUE     Y

With control class: TuneControlRandom

Imputation value: 1

[Tune-x] 1: nrounds=323; max_depth=7; eta=0.212; lambda=0.166

[Tune-y] 1: mmce.test.mean=0.0534750; time: 0.6 min

[Tune-x] 2: nrounds=129; max_depth=3; eta=0.275; lambda=0.213

[Tune-y] 2: mmce.test.mean=0.0518250; time: 0.1 min

[Tune-x] 3: nrounds=297; max_depth=7; eta=0.254; lambda=0.105

[Tune-y] 3: mmce.test.mean=0.0537750; time: 0.5 min

[Tune-x] 4: nrounds=374; max_depth=6; eta=0.468; lambda=0.128

[Tune-y] 4: mmce.test.mean=0.0543750; time: 0.6 min

[Tune-x] 5: nrounds=372; max_depth=5; eta=0.45; lambda=0.196

[Tune-y] 5: mmce.test.mean=0.0543500; time: 0.5 min

[Tune] Result: nrounds=129; max_depth=3; eta=0.275; lambda=0.213 :
mmce.test.mean=0.0518250
```

```
      Targeted Population (%) Incremental Uplift (%) Observed Uplift (%)
 [1,]                     0.1               4.401325          46.2543641
 [2,]                     0.2               6.709495          15.5597789
 [3,]                     0.3               7.300102           2.6841312
 [4,]                     0.4               7.633289           1.2506503
 [5,]                     0.5               7.966708           1.5166835
 [6,]                     0.6               8.149320           1.3399816
 [7,]                     0.7               8.291721           0.8982036
 [8,]                     0.8               8.490802           1.2121212
 [9,]                     0.9               8.883956           3.3406918
[10,]                     1.0               9.986970           9.8485544
attr(,"class")
[1] "print.PerformanceUplift"
```

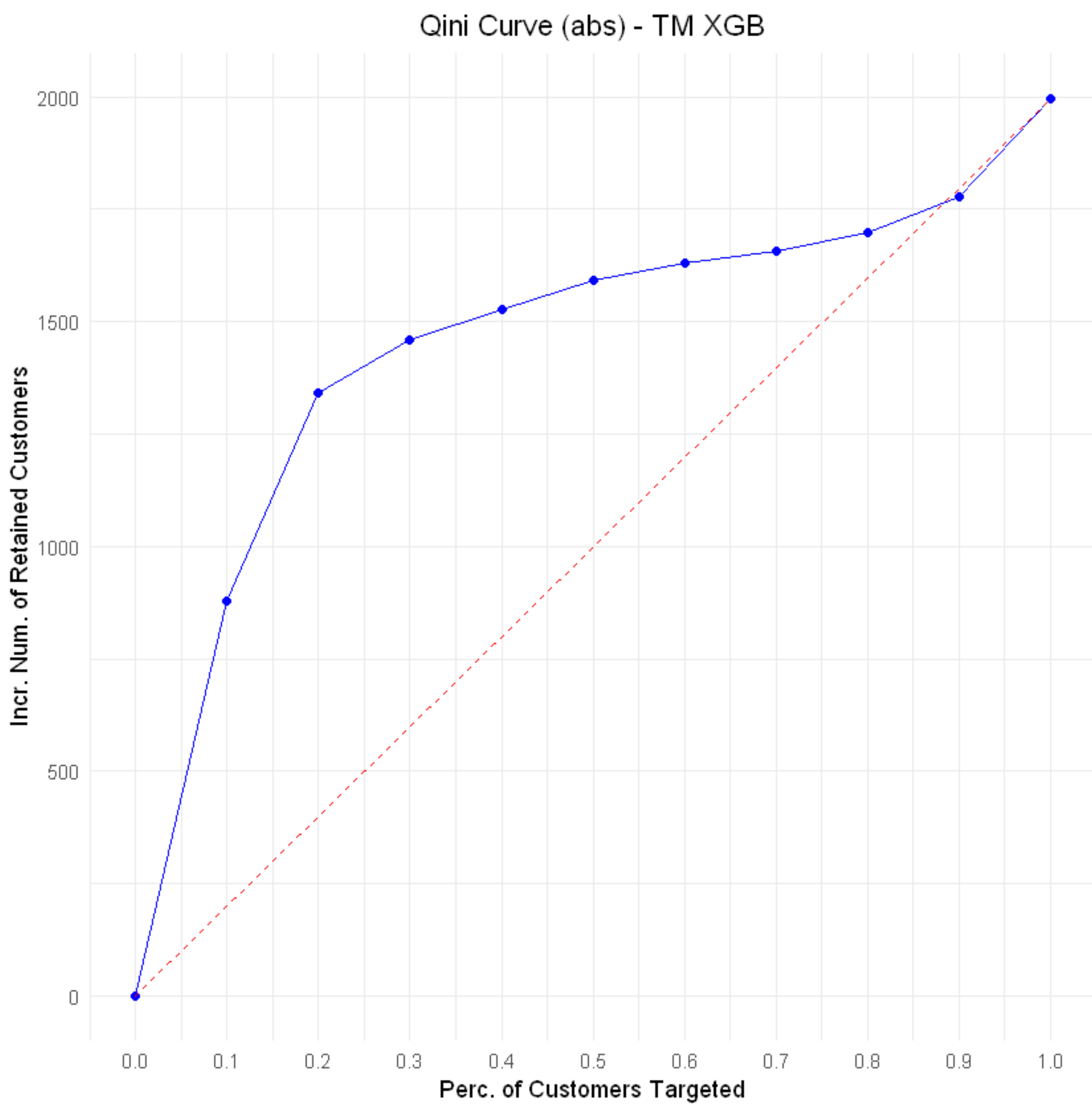
0.288888888888889

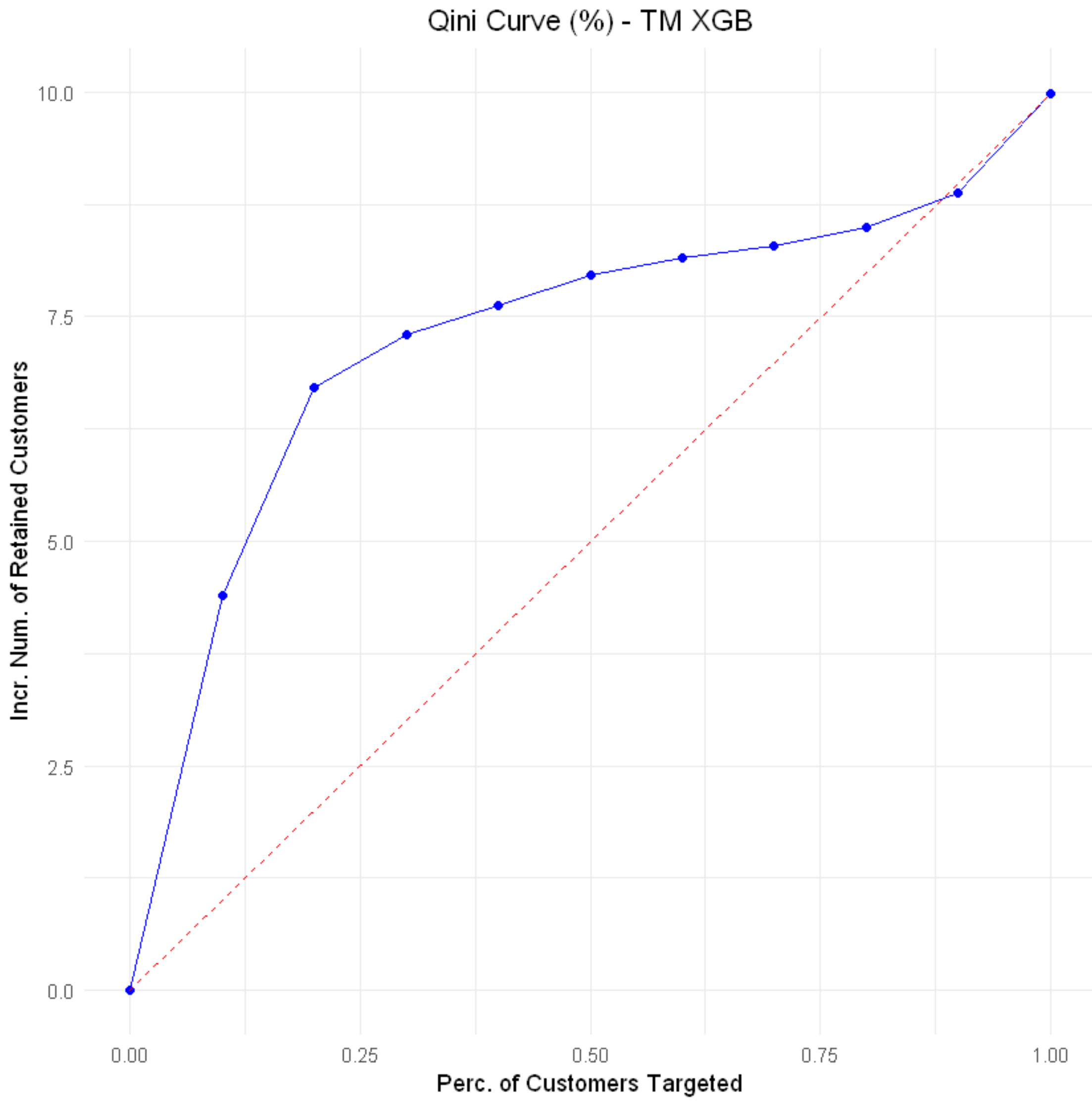
2.32324912619324



[24]:
```
# Plotting Qini curve and Qini Coeff on the test set - scrivere funzione che lo␣
↪faccia
# in automatico

df=data.frame(matrix(nrow=10, ncol=3))
df[,1]=perf_xgb[[1]]
df[,2]=round(perf_xgb[[6]],2)
df[,3]=round(perf_xgb[[7]],2)
colnames(df)=c("Dec", "num.incr", "perc.incr")
firstrow=numeric(3)
df=rbind(firstrow,df)

##Plot Qini curves
```

```
qini_curve1<-ggplot(df, aes(x=Dec, y=num.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (abs) - TM XGB", y="Incr. Num. of Retained␣
↪Customers", x="Perc. of Customers Targeted")+
  scale_x_continuous(breaks=seq(0, 1, 0.1))+geom_segment(x = 0, y=0, xend=1,␣
↪yend=df[11,2], color="red",
                                                                  linetype="dashed",␣
↪size=0.5)
qini_curve1

qini_curve2<-ggplot(df, aes(x=Dec, y=perc.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve (%) - TM XGB", y="Incr. Num. of Retained␣
↪Customers", x="Perc. of Customers Targeted")+
  xlim(0, 1)+geom_segment(x = 0, y=0, xend=1, yend=df[11,3], color="red",
                              linetype="dashed", size=0.5)
qini_curve2
```


Qini Curve (abs) - TM XGB
Incr. Num. of Retained Customers
2000
1500
1000
500
0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Perc. of Customers Targeted



5.2 Single Model with Interactions

5.2.1 Intuition

[25]:
```
# Intuition
# logit_model_inter<-glm(y ~ u_weekly_utilisation + u_rating_given + treat +
↪u_weekly_utilisation*treat + u_rating_given*treat , family=
↪binomial(link=logit), data=data)
# data_interaction=data
# data_interaction$pred= logit_model_inter %>% predict(data_interaction, type =
↪"response")
# print('Estimated Probabilities')
```

```
# plot_ly(x=data_interaction$u_weekly_utilisation,␣
↪y=data_interaction$u_rating_given, z=data_interaction$pred, ␣
↪type="scatter3d", mode="markers", color=data_interaction$treat)
# print('Estimated Probabilities for treated and non treated customers')
```

5.2.2 Basic Model

[26]:
```
### 3.1 Basic Single Model ####

#Creating a copy of the train and test sets
train_interuplift=train
test_interuplift=test

#Estimating the model
intermodel<-InterUplift(train, treat='treat', outcome='y', predictors=features,␣
↪input = "all")

print(intermodel)
summary(intermodel)
```

```
Call:  InterUplift(data = train, treat = "treat", outcome = "y", predictors =
features,
    input = "all")

Coefficients:
               (Intercept)                       treat
                  0.272898                    1.373958
                 u_gender2                       u_age
                  0.015169                   -0.133078
      u_weekly_utilisation           u_sub_utilisation
                  0.578915                    0.859479
            u_format_pref2              u_format_pref3
                 -0.695017                   -0.779524
             u_genre_pref2               u_genre_pref3
                 -0.614695                   -0.495697
             u_genre_pref4               u_genre_pref5
                 -0.002982                   -0.559332
             u_genre_pref6               u_genre_pref7
                 -0.559085                   -0.582062
            u_rating_given                u_other_sub1
                  0.305304                   -0.368569
             u_occupation2               u_occupation3
                 -0.399442                   -0.334034
             u_occupation4               u_occupation5
                 -0.075042                    0.156067
           treat:u_gender2                 treat:u_age
```

```
               -0.028452                      -0.070075
treat:u_weekly_utilisation     treat:u_sub_utilisation
               -0.333476                      -0.308320
      treat:u_format_pref2        treat:u_format_pref3
                0.366416                       0.467264
       treat:u_genre_pref2         treat:u_genre_pref3
                0.163756                       0.096446
       treat:u_genre_pref4         treat:u_genre_pref5
                0.087212                       0.388027
       treat:u_genre_pref6         treat:u_genre_pref7
                0.397965                       0.338512
      treat:u_rating_given          treat:u_other_sub1
               -0.123628                       0.405361
       treat:u_occupation2         treat:u_occupation3
                0.092037                       0.056737
       treat:u_occupation4         treat:u_occupation5
                0.262253                       0.144358

Degrees of Freedom: 59999 Total (i.e. Null);  59962 Residual
Null Deviance:      53780
Residual Deviance: 44170        AIC: 44250


Call:
InterUplift(data = train, treat = "treat", outcome = "y", predictors = features,
    input = "all")

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.5502   0.2373   0.4045   0.5885   2.0670

Coefficients:
                            Estimate Std. Error z value             Pr(>|z|)
(Intercept)                 0.272898   0.091033   2.998             0.002719
treat                       1.373958   0.137915   9.962 < 0.0000000000000002
u_gender2                   0.015169   0.033610   0.451             0.651751
u_age                      -0.133078   0.019042  -6.989   0.0000000000027757
u_weekly_utilisation        0.578915   0.009071  63.823 < 0.0000000000000002
u_sub_utilisation           0.859479   0.057792  14.872 < 0.0000000000000002
u_format_pref2             -0.695017   0.035233 -19.726 < 0.0000000000000002
u_format_pref3             -0.779524   0.055000 -14.173 < 0.0000000000000002
u_genre_pref2              -0.614695   0.063459  -9.687 < 0.0000000000000002
u_genre_pref3              -0.495697   0.064691  -7.663   0.0000000000000182
u_genre_pref4              -0.002982   0.067662  -0.044             0.964842
u_genre_pref5              -0.559332   0.064196  -8.713 < 0.0000000000000002
u_genre_pref6              -0.559085   0.064432  -8.677 < 0.0000000000000002
u_genre_pref7              -0.582062   0.064145  -9.074 < 0.0000000000000002
u_rating_given              0.305304   0.011786  25.904 < 0.0000000000000002
```

```
u_other_sub1                -0.368569   0.033067 -11.146 < 0.0000000000000002
u_occupation2               -0.399442   0.072460  -5.513   0.0000000353532508
u_occupation3               -0.334034   0.076309  -4.377   0.0000120114218655
u_occupation4               -0.075042   0.080165  -0.936             0.349226
u_occupation5                0.156067   0.142228   1.097             0.272510
treat:u_gender2             -0.028452   0.049798  -0.571             0.567768
treat:u_age                 -0.070075   0.027545  -2.544             0.010959
treat:u_weekly_utilisation -0.333476   0.012329 -27.048 < 0.0000000000000002
treat:u_sub_utilisation     -0.308320   0.085278  -3.615             0.000300
treat:u_format_pref2         0.366416   0.051960   7.052   0.0000000000017642
treat:u_format_pref3         0.467264   0.081380   5.742   0.0000000093704777
treat:u_genre_pref2          0.163756   0.092141   1.777             0.075530
treat:u_genre_pref3          0.096446   0.093315   1.034             0.301343
treat:u_genre_pref4          0.087212   0.099147   0.880             0.379065
treat:u_genre_pref5          0.388027   0.095115   4.080   0.0000451246435685
treat:u_genre_pref6          0.397965   0.095046   4.187   0.0000282548193731
treat:u_genre_pref7          0.338512   0.094394   3.586             0.000336
treat:u_rating_given        -0.123628   0.017239  -7.171   0.0000000000007433
treat:u_other_sub1           0.405361   0.048857   8.297 < 0.0000000000000002
treat:u_occupation2          0.092037   0.111999   0.822             0.411207
treat:u_occupation3          0.056737   0.117508   0.483             0.629215
treat:u_occupation4          0.262253   0.124432   2.108             0.035065
treat:u_occupation5          0.144358   0.208748   0.692             0.489227

(Intercept)                 **
treat                       ***
u_gender2
u_age                       ***
u_weekly_utilisation        ***
u_sub_utilisation           ***
u_format_pref2              ***
u_format_pref3              ***
u_genre_pref2               ***
u_genre_pref3               ***
u_genre_pref4
u_genre_pref5               ***
u_genre_pref6               ***
u_genre_pref7               ***
u_rating_given              ***
u_other_sub1                ***
u_occupation2               ***
u_occupation3               ***
u_occupation4
u_occupation5
treat:u_gender2
treat:u_age                 *
treat:u_weekly_utilisation ***
treat:u_sub_utilisation     ***
```

```
treat:u_format_pref2       ***
treat:u_format_pref3       ***
treat:u_genre_pref2        .
treat:u_genre_pref3
treat:u_genre_pref4
treat:u_genre_pref5        ***
treat:u_genre_pref6        ***
treat:u_genre_pref7        ***
treat:u_rating_given       ***
treat:u_other_sub1         ***
treat:u_occupation2
treat:u_occupation3
treat:u_occupation4        *
treat:u_occupation5
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 53780  on 59999  degrees of freedom
Residual deviance: 44175  on 59962  degrees of freedom
AIC: 44251

Number of Fisher Scoring iterations: 5
```

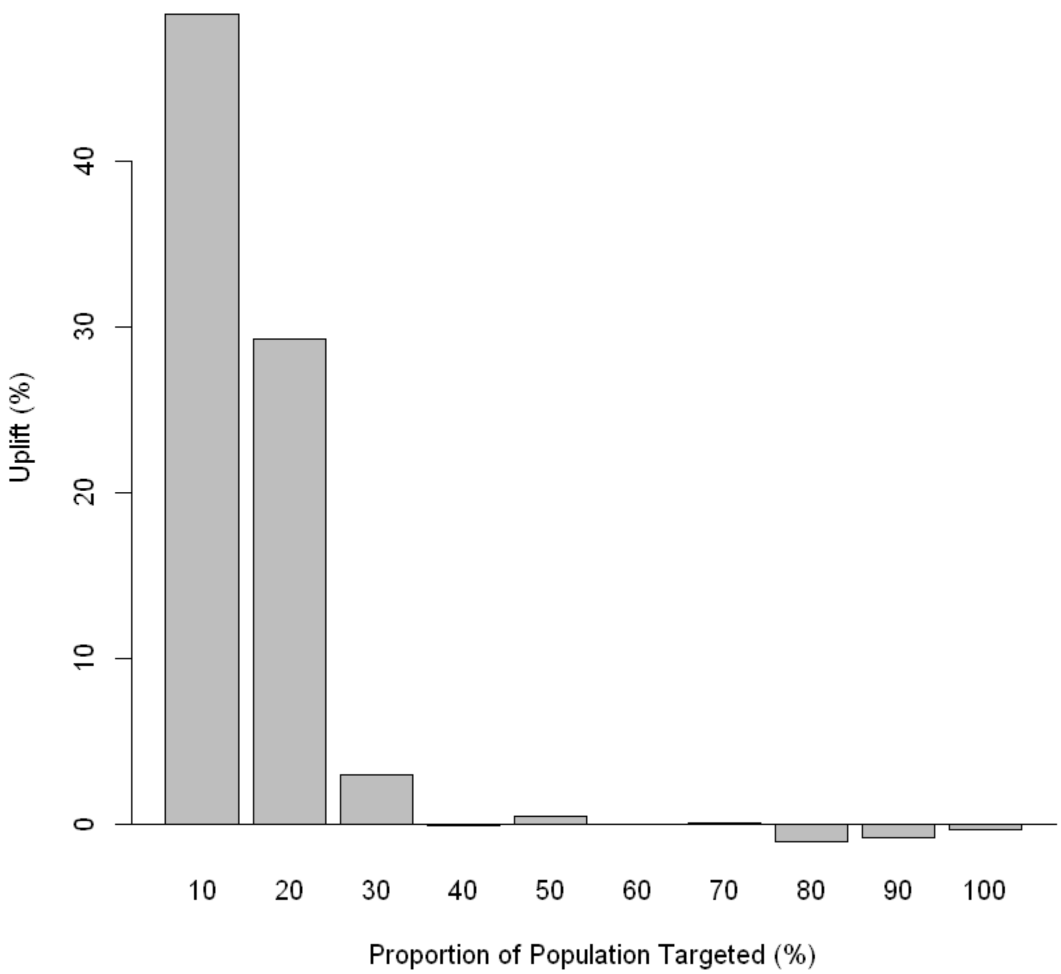
[27]:
```
#Extracting predictions for train data
pred_intermodel= predict(intermodel, train_interuplift, treat='treat')
train_interuplift$pred_intermodel=pred_intermodel

#Eveluating the model performance
perf_intermodel=PerformanceUplift(data = train_interuplift, treat = "treat",
                                  outcome = "y", prediction =
 ↪"pred_intermodel", equal.intervals = TRUE, nb.group = 10)


perf_intermodel
barplot.PerformanceUplift(perf_intermodel)

QiniArea(perf_intermodel)
```

```
      Targeted Population (%) Incremental Uplift (%) Observed Uplift (%)
 [1,]                     0.1               5.219424         48.89500138
 [2,]                     0.2               8.126014         29.25379543
 [3,]                     0.3               8.370911          2.94559490
 [4,]                     0.4               8.214226         -0.12463092
 [5,]                     0.5               8.284826          0.46930239
```

```
 [6,]                     0.6               8.350635          0.02466575
 [7,]                     0.7               8.187759          0.07101021
 [8,]                     0.8               8.036696         -1.07107660
 [9,]                     0.9               8.036657         -0.84510589
[10,]                     1.0               7.934585         -0.37228254
attr(,"class")
[1] "print.PerformanceUplift"
```

0.688888888888889

3.47399867788024



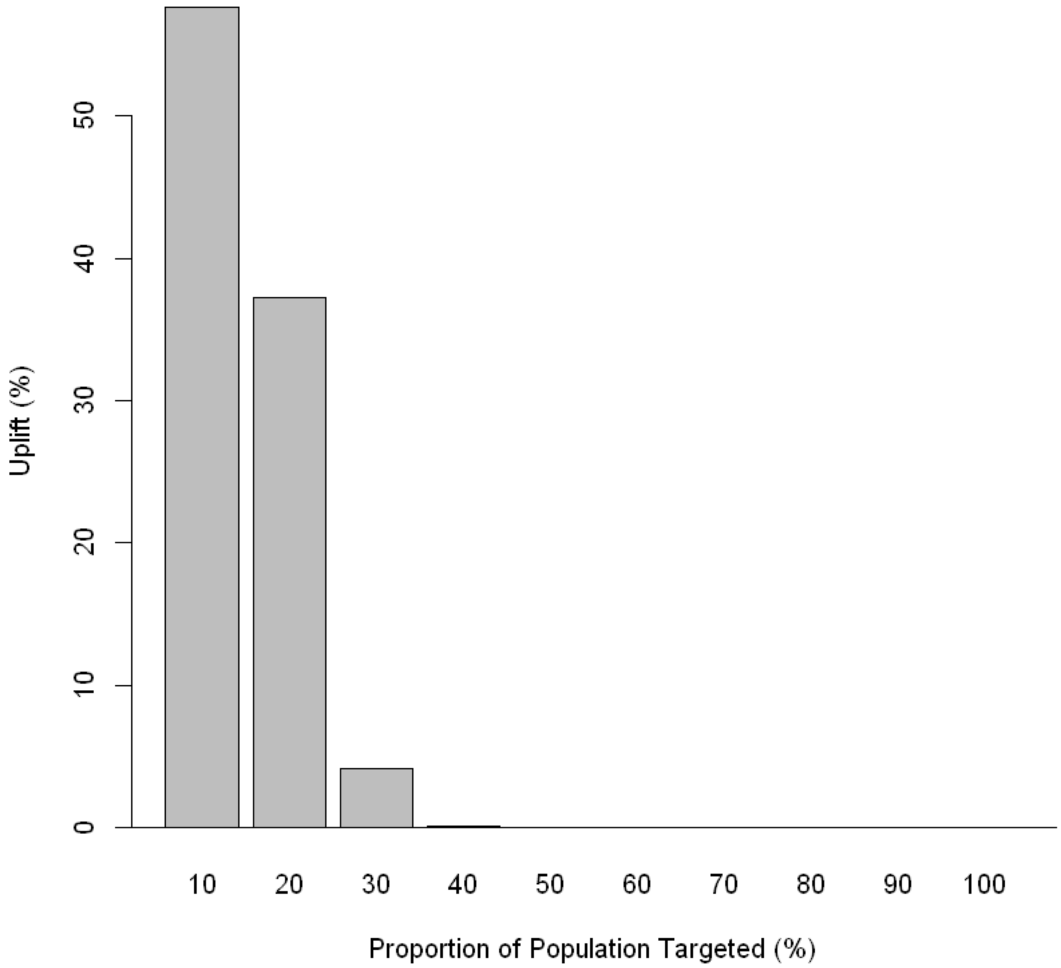
[28]:
```
# Test set
```

```
#Extracting predictions for test  data
pred_intermodel_test= predict(intermodel, test_interuplift, treat='treat')
test_interuplift$pred_intermodel=pred_intermodel_test

#Eveluating the model performance on the test set
perf_intermodel=PerformanceUplift(data = test_interuplift, treat = "treat",
                                  outcome = "y", prediction =␣
 ↪"pred_intermodel", equal.intervals = TRUE, nb.group = 10)


perf_intermodel
barplot.PerformanceUplift(perf_intermodel)

QiniArea(perf_intermodel)
```

```
      Targeted Population (%) Incremental Uplift (%) Observed Uplift (%)
 [1,]                     0.1               6.126173         57.65277950
 [2,]                     0.2               9.669139         37.24125619
 [3,]                     0.3              10.036062          4.09055920
 [4,]                     0.4              10.128185          0.05068424
 [5,]                     0.5              10.111556          0.00000000
 [6,]                     0.6              10.164670          0.00000000
 [7,]                     0.7              10.045130          0.00000000
 [8,]                     0.8              10.064818          0.00000000
 [9,]                     0.9              10.038281          0.00000000
[10,]                     1.0               9.986970          0.00000000
attr(,"class")
[1] "print.PerformanceUplift"
```

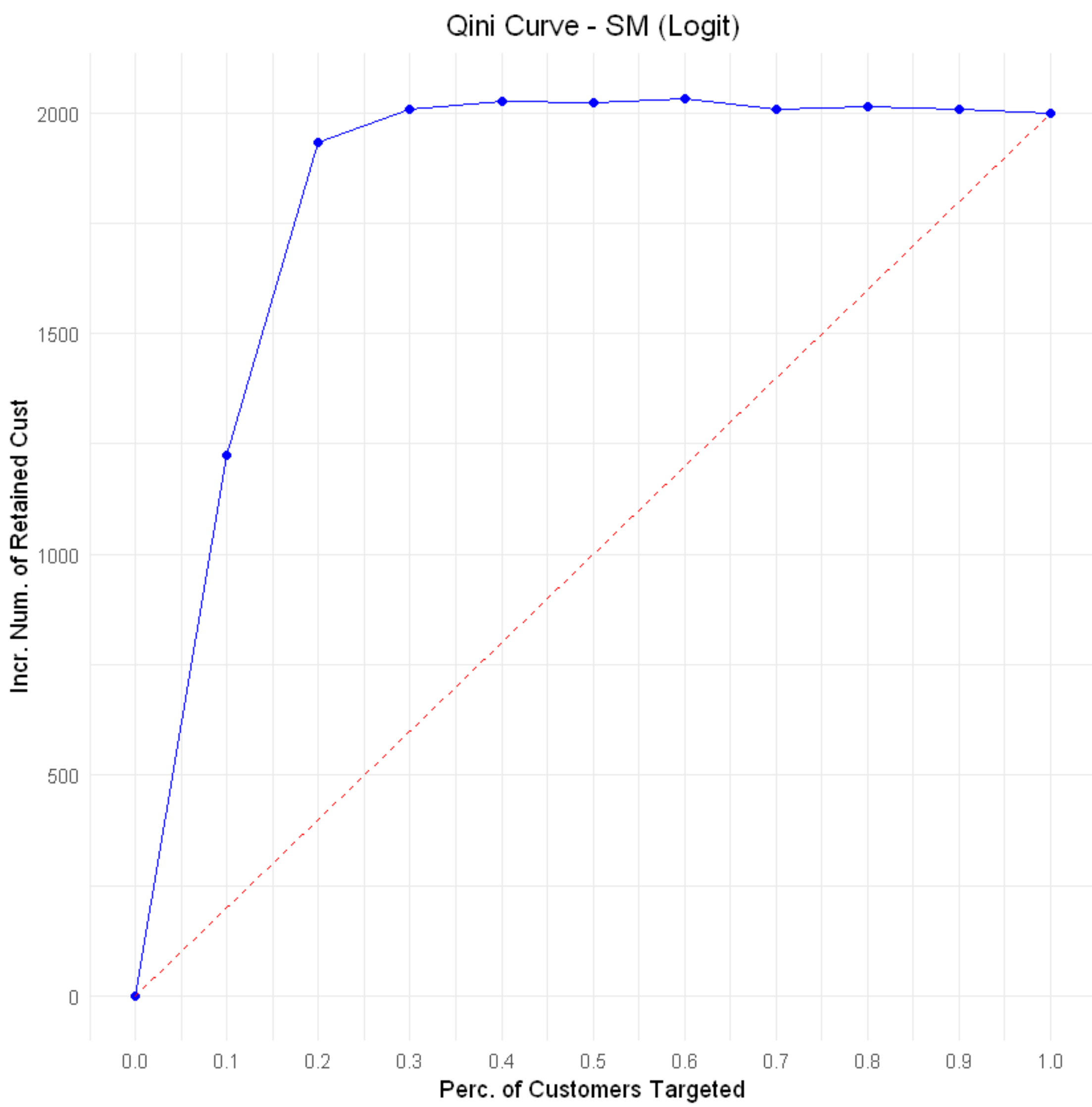
0.816496580927726

4.09966707616079

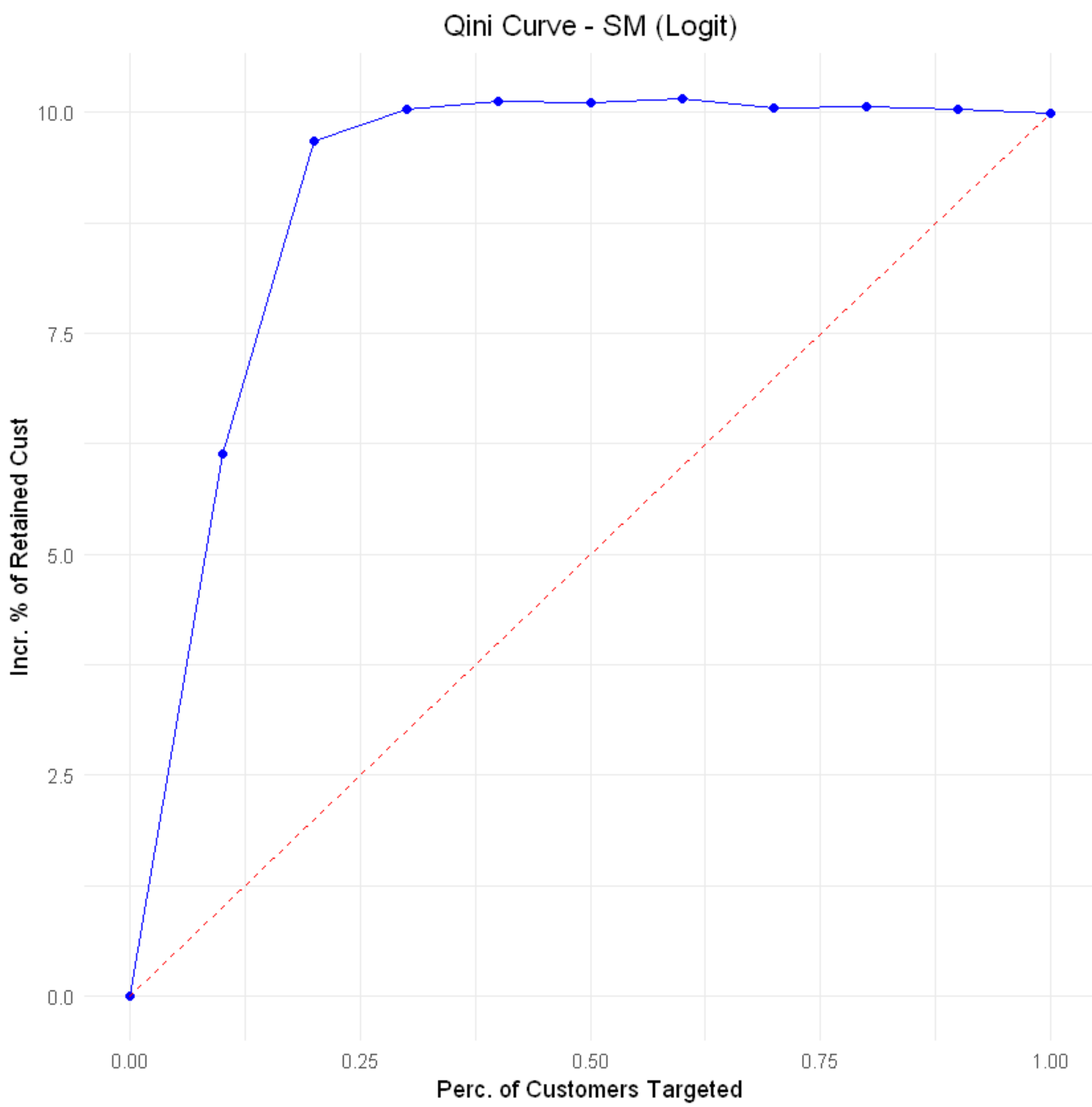


[29]:
```
# Plotting Qini curve and Qini Coeff on the test set - scrivere funzione che lo␣
↪faccia
# in automatico

df=data.frame(matrix(nrow=10, ncol=3))
df[,1]=perf_intermodel[[1]]
df[,2]=round(perf_intermodel[[6]],2)
df[,3]=round(perf_intermodel[[7]],2)
colnames(df)=c("Dec", "num.incr", "perc.incr")
firstrow=numeric(3)
df=rbind(firstrow,df)
```

```
# Plot Qini curves
qini_curve_1<-ggplot(df, aes(x=Dec, y=num.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve - SM (Logit)", y="Incr. Num. of Retained␣
↪Cust", x="Perc. of Customers Targeted")+
  scale_x_continuous(breaks=seq(0, 1, 0.1))+geom_segment(x = 0, y=0, xend=1,␣
↪yend=df[11,2], color="red",
                                                                    linetype="dashed",␣
↪size=0.5)
qini_curve_1


qini_curve_2<-ggplot(df, aes(x=Dec, y=perc.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve - SM (Logit)", y="Incr. % of Retained Cust",␣
↪x="Perc. of Customers Targeted")+
  xlim(0, 1)+geom_segment(x = 0, y=0, xend=1, yend=df[11,3], color="red",
                linetype="dashed", size=0.5)
qini_curve_2

# Qini area

QiniArea(perf_intermodel)
```



4.09966707616079



5.2.3 Model Selection

[31]:
```
## 3.2 Model selection ####



# Understanding the function LassoPath
# formula=intermodel[[23]]
# my_path=LassoPath(train_interuplift, formula)
# my_path_mod=LassoPath_mod(train_interuplift, formula)

#Finding the optimal set of features
# La funzione BestFeatures() non funziona con variabili categoriche inserite
↪come fattori, e dunque vanno messe one hot encoded come per l'xgb
```

```
# Penso che per il momento la funzione non metta una categoria come baseline e␣
↪dunque sputa il set di warnings che si vedono sotto (relativi alla␣
↪multicollinearità delle featuers)
# Capire come può essere risolta questa cosa (provare a rimuovere una categoria␣
↪per ogni variabili dela dataset oh, oppure modificare il source code della␣
↪funzione affinché lavori con variabili
# categoriche fattorizzate).

inter_opt_feat=BestFeatures(data=data_oh, treat='treat', outcome='y',␣
↪predictors=features_oh, rank.precision = 2,
             equal.intervals = FALSE, nb.group = 10,
             validation = TRUE, p = 0.4)

# La funzione BestFeatures va a trovare un set di features ottimo per il␣
↪modello, utilizzando
# la cross validation (semplce train vs test) e considerando il Qini coeff.␣
↪Unico problema è che parte dall'intero dataset ed utilizza
# train e test set creati da zero (fa nuovamente lo split internamente). Noi␣
↪abbiamo bisogno che utilizzi
# il train e il test set che abbiamo già creato e utilizzato negli altri␣
↪modelli.
# Bisogna dunque modificare la funzione affinché lavori in questo modo.

# Writing the corresponding formula for the model
formula_final_inter=as.formula(paste("y~", paste(inter_opt_feat, collapse="+")))
```

```
Warning message in PerformanceUplift(valid, treat, outcome, "lambda.pred",
rank.precision = rank.precision, :
"The number of unique predictions will be used as the number of groups"
Warning message in PerformanceUplift(valid, treat, outcome, "lambda.pred",
rank.precision = rank.precision, :
"The number of unique predictions will be used as the number of groups"
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
```

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

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

[32]:
```
###INTERUPLIFT FORMULA: una versione leggermente modificata della funzione␣
↪InterUplift()
# che permette di stimare un modello partendo da una formula prespecificata␣
↪dall'utente

InterUplift.formula <- function(formula, treat, data, ...){

  # Formula interface to InterUplift.
  if (!inherits(formula, "formula"))
    stop("Method is only for formula objects")

  mf <- match.call(expand.dots = FALSE)
  args <- match(c("formula", "data"), names(mf), 0)
  mf <- mf[c(1, args)]
  mf$drop.unused.levels <- TRUE
  mf[[1]] <- as.name("model.frame")
  mf <- eval.parent(mf)

  Terms <- attr(mf, "terms")
  Terms <- names(attr(Terms,"dataClasses"))

  if (length(intersect(treat,colnames(data))) == 0)
    stop("InterUplift: data does not include the control/treatment variable␣
↪treat).")

  outcome <- Terms[1]
  predictors <- Terms[-1]
  fit <- InterUplift(data=data, treat=treat, outcome=outcome,␣
↪predictors=predictors, input = "all", ...)


  cl <- match.call()
  cl[[1]] <- as.name("InterUplift")
  fit$call <- cl

  return(fit)
}
```

[34]:

```
# Train
final_intermodel_train<-InterUplift.formula(formula=formula_final_inter,␣
↪treat="treat", data=train_oh)
print(final_intermodel_train)
summary(final_intermodel_train)


pred_intermodel_final= predict(final_intermodel_train, train_interuplift,␣
↪treat='treat')
train_interuplift$pred_intermodel_final=pred_intermodel_final
perf_intermodel_final=PerformanceUplift(data = train_interuplift, treat =␣
↪"treat",
                                  outcome = "y", prediction =␣
↪"pred_intermodel_final", equal.intervals = TRUE, nb.group = 10)

perf_intermodel_final
barplot.PerformanceUplift(perf_intermodel_final)
QiniArea(perf_intermodel_final)


# Test

final_intermodel_test<-InterUplift.formula(formula=formula_final_inter,␣
↪treat="treat", data=test_interuplift)
print(final_intermodel_test)
summary(final_intermodel_test)


pred_intermodel_final= predict(final_intermodel_test, test_interuplift,␣
↪treat='treat')
test_interuplift$pred_intermodel_final=pred_intermodel_final
perf_intermodel_final=PerformanceUplift(data = test_interuplift, treat =␣
↪"treat",
                                        outcome = "y", prediction =␣
↪"pred_intermodel_final", equal.intervals = TRUE, nb.group = 10)
perf_intermodel_final
barplot.PerformanceUplift(perf_intermodel_final)
QiniArea(perf_intermodel_final)


# Holdout - Per ora non lo abbiamo
```

```
Call:  InterUplift(formula = formula_final_inter, treat = "treat", data =
train_oh)

Coefficients:
```

```
              (Intercept)                      treat
                 -0.73761                    2.35163
               u_gender_1                 u_gender_2
                 -0.01517                         NA
          u_format_pref_2            u_format_pref_3
                 -0.69502                   -0.77952
            u_genre_pref_1             u_genre_pref_2
                  0.58206                   -0.03263
            u_genre_pref_3             u_genre_pref_4
                  0.08637                    0.57908
            u_genre_pref_5             u_genre_pref_6
                  0.02273                    0.02298
            u_genre_pref_7              u_other_sub_0
                       NA                    0.36857
             u_other_sub_1             u_occupation_1
                       NA                    0.07504
            u_occupation_2             u_occupation_3
                 -0.32440                   -0.25899
            u_occupation_5                      u_age
                  0.23111                   -0.13308
      u_weekly_utilisation          u_sub_utilisation
                  0.57892                    0.85948
            u_rating_given             u_occupation_4
                  0.30530                         NA
          treat:u_gender_1           treat:u_gender_2
                  0.02845                         NA
     treat:u_format_pref_2      treat:u_format_pref_3
                  0.36642                    0.46726
      treat:u_genre_pref_1       treat:u_genre_pref_2
                 -0.33851                   -0.17476
      treat:u_genre_pref_3       treat:u_genre_pref_4
                 -0.24207                   -0.25130
      treat:u_genre_pref_5       treat:u_genre_pref_6
                  0.04952                    0.05945
      treat:u_genre_pref_7        treat:u_other_sub_0
                       NA                   -0.40536
       treat:u_other_sub_1       treat:u_occupation_1
                       NA                   -0.26225
      treat:u_occupation_2       treat:u_occupation_3
                 -0.17022                   -0.20552
      treat:u_occupation_5                treat:u_age
                 -0.11790                   -0.07007
treat:u_weekly_utilisation    treat:u_sub_utilisation
                 -0.33348                   -0.30832
      treat:u_rating_given       treat:u_occupation_4
                 -0.12363                         NA

Degrees of Freedom: 59999 Total (i.e. Null);  59962 Residual
```

```
Null Deviance:      53780
Residual Deviance: 44170        AIC: 44250

Call:
InterUplift(formula = formula_final_inter, treat = "treat", data = train_oh)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.5502   0.2373   0.4045   0.5885   2.0670

Coefficients: (8 not defined because of singularities)
                          Estimate Std. Error z value             Pr(>|z|)
(Intercept)              -0.737606   0.096069  -7.678   0.0000000000000162
treat                     2.351633   0.142378  16.517 < 0.0000000000000002
u_gender_1               -0.015169   0.033610  -0.451             0.651751
u_gender_2                      NA         NA      NA                   NA
u_format_pref_2          -0.695017   0.035233 -19.726 < 0.0000000000000002
u_format_pref_3          -0.779524   0.055000 -14.173 < 0.0000000000000002
u_genre_pref_1            0.582062   0.064145   9.074 < 0.0000000000000002
u_genre_pref_2           -0.032633   0.058848  -0.555             0.579218
u_genre_pref_3            0.086366   0.060166   1.435             0.151158
u_genre_pref_4            0.579080   0.063513   9.117 < 0.0000000000000002
u_genre_pref_5            0.022730   0.059604   0.381             0.702935
u_genre_pref_6            0.022977   0.059885   0.384             0.701205
u_genre_pref_7                  NA         NA      NA                   NA
u_other_sub_0             0.368569   0.033067  11.146 < 0.0000000000000002
u_other_sub_1                   NA         NA      NA                   NA
u_occupation_1            0.075042   0.080165   0.936             0.349226
u_occupation_2           -0.324400   0.051609  -6.286   0.0000000003262310
u_occupation_3           -0.258991   0.048684  -5.320   0.0000001038435889
u_occupation_5            0.231109   0.113519   2.036             0.041764
u_age                    -0.133078   0.019042  -6.989   0.0000000000027757
u_weekly_utilisation      0.578915   0.009071  63.823 < 0.0000000000000002
u_sub_utilisation         0.859479   0.057792  14.872 < 0.0000000000000002
u_rating_given            0.305304   0.011786  25.904 < 0.0000000000000002
u_occupation_4                  NA         NA      NA                   NA
treat:u_gender_1          0.028452   0.049798   0.571             0.567768
treat:u_gender_2                NA         NA      NA                   NA
treat:u_format_pref_2     0.366416   0.051960   7.052   0.0000000000017642
treat:u_format_pref_3     0.467264   0.081380   5.742   0.0000000093704777
treat:u_genre_pref_1     -0.338512   0.094394  -3.586             0.000336
treat:u_genre_pref_2     -0.174756   0.087214  -2.004             0.045096
treat:u_genre_pref_3     -0.242066   0.088445  -2.737             0.006202
treat:u_genre_pref_4     -0.251300   0.094711  -2.653             0.007970
treat:u_genre_pref_5      0.049515   0.090334   0.548             0.583596
treat:u_genre_pref_6      0.059453   0.090279   0.659             0.510188
treat:u_genre_pref_7            NA         NA      NA                   NA
```

```
treat:u_other_sub_0        -0.405361   0.048857  -8.297 < 0.0000000000000002
treat:u_other_sub_1               NA         NA      NA                 NA
treat:u_occupation_1       -0.262253   0.124432  -2.108           0.035065
treat:u_occupation_2       -0.170216   0.078575  -2.166           0.030289
treat:u_occupation_3       -0.205517   0.074168  -2.771           0.005589
treat:u_occupation_5       -0.117896   0.164829  -0.715           0.474447
treat:u_age                -0.070075   0.027545  -2.544           0.010959
treat:u_weekly_utilisation -0.333476   0.012329 -27.048 < 0.0000000000000002
treat:u_sub_utilisation    -0.308320   0.085278  -3.615           0.000300
treat:u_rating_given       -0.123628   0.017239  -7.171   0.0000000000007433
treat:u_occupation_4              NA         NA      NA                 NA

(Intercept)                ***
treat                      ***
u_gender_1
u_gender_2
u_format_pref_2            ***
u_format_pref_3            ***
u_genre_pref_1             ***
u_genre_pref_2
u_genre_pref_3
u_genre_pref_4             ***
u_genre_pref_5
u_genre_pref_6
u_genre_pref_7
u_other_sub_0              ***
u_other_sub_1
u_occupation_1
u_occupation_2             ***
u_occupation_3             ***
u_occupation_5             *
u_age                      ***
u_weekly_utilisation       ***
u_sub_utilisation          ***
u_rating_given             ***
u_occupation_4
treat:u_gender_1
treat:u_gender_2
treat:u_format_pref_2      ***
treat:u_format_pref_3      ***
treat:u_genre_pref_1       ***
treat:u_genre_pref_2       *
treat:u_genre_pref_3       **
treat:u_genre_pref_4       **
treat:u_genre_pref_5
treat:u_genre_pref_6
treat:u_genre_pref_7
treat:u_other_sub_0        ***
```

```
treat:u_other_sub_1
treat:u_occupation_1       *
treat:u_occupation_2       *
treat:u_occupation_3       **
treat:u_occupation_5
treat:u_age                *
treat:u_weekly_utilisation ***
treat:u_sub_utilisation    ***
treat:u_rating_given       ***
treat:u_occupation_4
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 53780  on 59999  degrees of freedom
Residual deviance: 44175  on 59962  degrees of freedom
AIC: 44251

Number of Fisher Scoring iterations: 5
```

```
Error in eval(predvars, data, env): oggetto "u_gender_1" non trovato
Traceback:

1. predict(final_intermodel_train, train_interuplift, treat = "treat")
2. predict.InterUplift(final_intermodel_train, train_interuplift,
 .     treat = "treat")
3. predict.glm(object, newdata = data1, type = "response", …)
4. predict.lm(object, newdata, se.fit, scale = 1, type = if (type ==
 .     "link") "response" else type, terms = terms, na.action = na.action)
5. model.frame(Terms, newdata, na.action = na.action, xlev = object$xlevels)
6. model.frame.default(Terms, newdata, na.action = na.action, xlev =␣
 ↪object$xlevels)
7. eval(predvars, data, env)
8. eval(predvars, data, env)
```

[ ]:
```
# Plotting Qini curve and Qini Coeff on the test set - scrivere funzione che lo␣
 ↪faccia
# in automatico

df=data.frame(matrix(nrow=10, ncol=3))
df[,1]=perf_intermodel_final[[1]]
df[,2]=round(perf_intperf_intermodel_finalermodel[[6]],2)
df[,3]=round(perf_intermodel_final[[7]],2)
colnames(df)=c("Dec", "num.incr", "perc.incr")
```

```
firstrow=numeric(3)
df=rbind(firstrow,df)


# Plot Qini curves
qini_curve_1<-ggplot(df, aes(x=Dec, y=num.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve - SM Logit (opt)", y="Incr. Num. of Retained␣
↪Cust", x="Perc. of Customers Targeted")+
  scale_x_continuous(breaks=seq(0, 1, 0.1))+geom_segment(x = 0, y=0, xend=1,␣
↪yend=df[11,2], color="red",
                                                         linetype="dashed",␣
↪size=0.5)
qini_curve_1


qini_curve_2<-ggplot(df, aes(x=Dec, y=perc.
↪incr))+geom_point(color="blue")+geom_line(color="blue")+
  mytheme+labs(title="Qini Curve - SM (Logit)", y="Incr. % of Retained Cust",␣
↪x="Perc. of Customers Targeted")+
  xlim(0, 1)+geom_segment(x = 0, y=0, xend=1, yend=df[11,3], color="red",
               linetype="dashed", size=0.5)
qini_curve_2
```