Bank Telemarketing Dataset

Content

A. Introduction

Telemarketing is a method of selling products and services over the phone to customers. It has always been a controversial approach. On one hand, it is easy to directly reach out to customers and also cheaper than other marketing methods. On the other hand, it has bad reputations of damaging the company's image and some of the startup costs are very expensive.

In this project, we are looking into how other factors can affect the outcome of telemarketing campaigns for a specific institution, Portuguese retail bank, and make prediction based on our model. The main focus of this project is incredibly interesting since we typically feel annoyed by telemarketing.

B. Problem Statement

Our main question is what is likely to be the outcome of the telemarketing campaigns based on the characteristics of the clients and the calls. Our goal is to predict if the client will subscribe (yes/no) to a term deposit (variable y).

Note: A term deposit is a type of deposit account held at a financial institution where money is locked up for some set period of time

C. Our Data

1. Data Source

- Dataset name: **Bank Tele-Marketing Data Set**
- Original Source of the Dataset: [Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014
- We retrieve the data from UCI Machine Learning Repository. The data is accessible **here**.

2. Background

- The data is collected from several telemarketing campaigns in which the Portuguese bank attempted to target customers through phone calls to sell long-term deposits.
- The dataset includes both the phone calls of which the bank executed and the phone calls of which clients contacted the help center.
- Each observation includes the outcome, whether or not the target customers subscribed the term deposit, and the characteristics of the customers and the phone calls themselves.

3. Variable Description

This dataset was collected from May 2008 to November 2010 with 41188 observations and 20 variables.

No.	Variable Name	Variable Definiton	Data Type	Units/Categories	Note
1	age	Client's age	Discrete	years	
2	job	Type of client's job	Categorical	admin, blue-collar, entrepreneur, housemaid, management, retired, self-employed, services, student, technician, unemployed	

3	marital	Marital status	Categorical	divorced, married, single	'divorced' means divorced or widowed
4	education	Education level	Categorical	basic.4y, basic.6y, basic.9y, high.school, illiterate, professional.course, university.degree	
5	default	Has credit in default?	Categorical	yes, no	
6	housing	Has housing loan?	Categorical	yes, no	
7	loan	Has personal loan?	Categorical	yes, no	
8	contact	Contact communication type	Categorical	cellular, telephone	
9	month	Last contact month of year	Categorical	jan, feb, mar, ..., nov, dec	
10	day_of_week	Last contact day of the week	Categorical	mon, tue, wed, thu, fri	
11	duration	Last contact duration	Discrete	seconds	This attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed.
12	campaign	Number of contacts performed during this campaign and for this client	Discrete	contacts	including last contact
13	pdays	Number of days that passed by after the client was last contacted from a previous campaign	Discrete	days	999 means client was not previously contacted
14	previous	Number of contacts performed before this campaign and for this client	Discrete	contacts	
15	poutcome	Outcome of the previous marketing campaign	Categorical	failure, success, nonexistent	

16	emp.var.rate	Employment variation rate - quarterly indicator	Continuous	-	Calculate the variation of employment rate ⇒ higher variation means the employment rate changes a lot (unstable economy)
17	cons.price.idx	Consumer price index - monthly indicator	Continuous	-	The average change in prices over time that consumers pay for a basket of goods and services
18	cons.conf.idx	Consumer confidence index - monthly indicator	Continuous	-	Defined as the degree of optimism about the state of the economy that consumers are expressing through their activities of saving and spending
19	euribor3m	Euribor 3 month rate - daily indicator	Continuous	-	Euribor is an overnight interbank rate comprised of the average interest rates from a panel of large European banks that are used for lending to one another in euros
20	nr.employed	Number of employees - quarterly indicator	Numeric	-	
21	y	Has the client subscribed to a term deposit?	Categorical	yes, no	

4. Problems with Data

1. There are two many categorical variables that aren't Bernoulli variables, and it would be complicated to interpret with too many of them

⇒ Possible solutions: change some of them (month, day_of_week, contact, etc) to other type of variables or group some of the categories together

1. Some of the data are not in its correct form (Bernoulli not broken into 0 and 1)
2. Some variables are terminologies
3. Some variables have many NAs
4. Some variables have special cases such as marital, duration, pdays

Read and explore the dataset

```
bankDf <- read.csv2("bank-additional-full.csv")
summary(bankDf)
```

```
##       age            job              marital           education        
##  Min.   :17.00   Length:41188       Length:41188       Length:41188      
##  1st Qu.:32.00   Class :character   Class :character   Class :character  
##  Median :38.00   Mode  :character   Mode  :character   Mode  :character  
##  Mean   :40.02                                                           
##  3rd Qu.:47.00                                                           
##  Max.   :98.00                                                           
##    default            housing              loan             contact         
##  Length:41188       Length:41188       Length:41188       Length:41188      
##  Class :character   Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character  
##                                                                             
##                                                                             
##                                                                             
##     month            day_of_week           duration         campaign     
##  Length:41188       Length:41188       Min.   :   0.0   Min.   : 1.000  
##  Class :character   Class :character   1st Qu.: 102.0   1st Qu.: 1.000  
##  Mode  :character   Mode  :character   Median : 180.0   Median : 2.000  
##                                        Mean   : 258.3   Mean   : 2.568  
##                                        3rd Qu.: 319.0   3rd Qu.: 3.000  
##                                        Max.   :4918.0   Max.   :56.000  
##      pdays          previous       poutcome          emp.var.rate      
##  Min.   :  0.0   Min.   :0.000   Length:41188       Length:41188      
##  1st Qu.:999.0   1st Qu.:0.000   Class :character   Class :character  
##  Median :999.0   Median :0.000   Mode  :character   Mode  :character  
##  Mean   :962.5   Mean   :0.173                                        
##  3rd Qu.:999.0   3rd Qu.:0.000                                        
##  Max.   :999.0   Max.   :7.000                                        
##  cons.price.idx     cons.conf.idx        euribor3m         nr.employed       
##  Length:41188       Length:41188       Length:41188       Length:41188      
##  Class :character   Class :character   Class :character   Class :character
```

```
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##       y
##  Length:41188
##  Class :character
##  Mode  :character
##
##
##
```

```
glimpse(bankDf)
```

```
## Rows: 41,188
## Columns: 21
## $ age            <int> 56, 57, 37, 40, 56, 45, 59, 41, 24, 25, 41, 25, 29,
57,…
## $ job            <chr> "housemaid", "services", "services", "admin.", "ser
vice…
## $ marital        <chr> "married", "married", "married", "married", "marrie
d", …
## $ education      <chr> "basic.4y", "high.school", "high.school", "basic.6y
", "…
## $ default        <chr> "no", "unknown", "no", "no", "no", "unknown", "no",
"un…
## $ housing        <chr> "no", "no", "yes", "no", "no", "no", "no", "no", "y
es",…
## $ loan           <chr> "no", "no", "no", "no", "yes", "no", "no", "no", "n
o", …
## $ contact        <chr> "telephone", "telephone", "telephone", "telephone",
"te…
## $ month          <chr> "may", "may", "may", "may", "may", "may", "may", "m
ay",…
## $ day_of_week    <chr> "mon", "mon", "mon", "mon", "mon", "mon", "mon", "m
on",…
## $ duration       <int> 261, 149, 226, 151, 307, 198, 139, 217, 380, 50, 55
, 22…
## $ campaign       <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1…
## $ pdays          <int> 999, 999, 999, 999, 999, 999, 999, 999, 999, 999, 9
99, …
## $ previous       <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0…
## $ poutcome       <chr> "nonexistent", "nonexistent", "nonexistent", "nonex
iste…
## $ emp.var.rate   <chr> "1.1", "1.1", "1.1", "1.1", "1.1", "1.1", "1.1", "1
.1",…
## $ cons.price.idx <chr> "93.994", "93.994", "93.994", "93.994", "93.994", "
93.9…
```

```
## $ cons.conf.idx  <chr> "-36.4", "-36.4", "-36.4", "-36.4", "-36.4", "-36.4
", "…
## $ euribor3m      <chr> "4.857", "4.857", "4.857", "4.857", "4.857", "4.857
", "…
## $ nr.employed    <chr> "5191", "5191", "5191", "5191", "5191", "5191", "51
91",…
## $ y              <chr> "no", "no", "no", "no", "no", "no", "no", "no", "no
", "…
```

Data Wrangling

Turn all "unknown" to NA value

```
bankDf <- bankDf %>% replace_with_na_all(condition = ~.x == "unknown")
```

Turn Bernoulli variables into 0 and 1 categories

```
bankDf <- rename(bankDf, telephone = contact)
bankDf <- rename(bankDf, deposit = y)

bankDf <- bankDf %>%
  #mutate(employed = ifelse(employed == "unemployed", 0, 1)) %>%
  mutate(default = ifelse(default == "yes", 1, 0)) %>%
  mutate(housing = ifelse(housing == "yes", 1, 0)) %>%
  mutate(loan = ifelse(loan == "yes", 1, 0)) %>%
  mutate(telephone = ifelse(telephone == "telephone", 1, 0)) %>%
  mutate(deposit = ifelse(deposit == "yes", 1, 0))
```

Turn other variables into its suitable types of variables

```
#bankDf$employed <- as.factor(bankDf$employed)
bankDf$job <- as.factor(bankDf$job)
bankDf$marital <- as.factor(bankDf$marital)
bankDf$education <- as.factor(bankDf$education)
bankDf$default <- as.factor(bankDf$default)
bankDf$housing <- as.factor(bankDf$housing)
bankDf$loan <- as.factor(bankDf$loan)
bankDf$telephone <- as.factor(bankDf$telephone)
bankDf$poutcome <- as.factor(bankDf$poutcome)
bankDf$month <- as.factor(bankDf$month)
bankDf$day_of_week <- as.factor(bankDf$day_of_week)

bankDf$previous <- as.numeric(bankDf$previous)
bankDf$emp.var.rate <- as.numeric(bankDf$emp.var.rate)
bankDf$cons.price.idx <- as.numeric(bankDf$cons.price.idx)
bankDf$cons.conf.idx <- as.numeric(bankDf$cons.conf.idx)
bankDf$euribor3m <- as.numeric(bankDf$euribor3m)
bankDf$nr.employed <- as.numeric(bankDf$nr.employed)

bankDf$pdays <- as.factor(bankDf$pdays)
```

Data Exploration

```
summary(bankDf)
```

```
##       age                  job            marital     
##  Min.   :17.00   admin.     :10422   divorced: 4612  
##  1st Qu.:32.00   blue-collar: 9254   married :24928  
##  Median :38.00   technician : 6743   single  :11568  
##  Mean   :40.02   services   : 3969   NA's    :   80  
##  3rd Qu.:47.00   management : 2924                   
##  Max.   :98.00   (Other)    : 7546                   
##                  NA's       :  330                   
##                education     default      housing        loan       teleph
one
##  university.degree  :12168   0   :32588   0   :18622   0   :33950   0:2614
4
##  high.school        : 9515   1   :    3   1   :21576   1   : 6248   1:1504
4
##  basic.9y           : 6045   NA's: 8597   NA's:  990   NA's:  990          
##  professional.course: 5243                                                 
##  basic.4y           : 4176                                                 
##  (Other)            : 2310                                                 
##  NA's               : 1731                                                 
##      month       day_of_week    duration         campaign          pdays   
##  may    :13769   fri:7827    Min.   :   0.0   Min.   : 1.000   999    :396
73
##  jul    : 7174   mon:8514    1st Qu.: 102.0   1st Qu.: 1.000   3      :  4
39
##  aug    : 6178   thu:8623    Median : 180.0   Median : 2.000   6      :  4
12
##  jun    : 5318   tue:8090    Mean   : 258.3   Mean   : 2.568   4      :  1
18
##  nov    : 4101   wed:8134    3rd Qu.: 319.0   3rd Qu.: 3.000   9      :   
64
##  apr    : 2632               Max.   :4918.0   Max.   :56.000   2      :   
61
##  (Other): 2016                                                 (Other):  4
21
##     previous            poutcome      emp.var.rate      cons.price.idx 
##  Min.   :0.000   failure    : 4252   Min.   :-3.40000   Min.   :92.20  
##  1st Qu.:0.000   nonexistent:35563   1st Qu.:-1.80000   1st Qu.:93.08  
##  Median :0.000   success    : 1373   Median : 1.10000   Median :93.75  
##  Mean   :0.173                       Mean   : 0.08189   Mean   :93.58  
##  3rd Qu.:0.000                       3rd Qu.: 1.40000   3rd Qu.:93.99  
##  Max.   :7.000                       Max.   : 1.40000   Max.   :94.77  
##                                                                        
##  cons.conf.idx     euribor3m      nr.employed      deposit      
##  Min.   :-50.8   Min.   :0.634   Min.   :4964   Min.   :0.0000  
##  1st Qu.:-42.7   1st Qu.:1.344   1st Qu.:5099   1st Qu.:0.0000  
##  Median :-41.8   Median :4.857   Median :5191   Median :0.0000  
##  Mean   :-40.5   Mean   :3.621   Mean   :5167   Mean   :0.1127  
##  3rd Qu.:-36.4   3rd Qu.:4.961   3rd Qu.:5228   3rd Qu.:0.0000  
##  Max.   :-26.9   Max.   :5.045   Max.   :5228   Max.   :1.0000  
## 
```

Make some decisions

We decide to remove those columns below: - `default` because it has too many NAs - `poutcome` (previous campaign's outcome) because it has too many "nonexistent" result - `pdays` (days after the customers were last contacted in the previous campaigns) because most of the customers had never been contacted before

```
bankDf <- bankDf %>%
  select(!default) %>%
  select(!poutcome) %>%
  select(!pdays)

bankDf <- na.omit(bankDf)
summary(bankDf)
```

```
##       age                 job            marital     
##  Min.   :17.00   admin.     :9937   divorced: 4302  
##  1st Qu.:32.00   blue-collar:8560   married :23183  
##  Median :38.00   technician :6380   single  :10760  
##  Mean   :39.86   services   :3716                   
##  3rd Qu.:47.00   management :2728                   
##  Max.   :98.00   retired    :1577                   
##                  (Other)    :5347                   
##                education     housing    loan       telephone     month      
##  basic.4y           : 4002   0:17667   0:32286   0:24441   may    :12794  
##  basic.6y           : 2204   1:20578   1: 5959   1:13804   jul    : 6630  
##  basic.9y           : 5856                                 aug    : 5822  
##  high.school        : 9244                                 jun    : 4846  
##  illiterate         :   18                                 nov    : 3898  
##  professional.course: 5100                                 apr    : 2436  
##  university.degree  :11821                                 (Other): 1819  
##  day_of_week    duration         campaign         previous   
##  fri:7224    Min.   :   0.0   Min.   : 1.000   Min.   :0.00  
##  mon:7927    1st Qu.: 102.0   1st Qu.: 1.000   1st Qu.:0.00  
##  thu:8011    Median : 180.0   Median : 2.000   Median :0.00  
##  tue:7481    Mean   : 258.2   Mean   : 2.567   Mean   :0.17  
##  wed:7602    3rd Qu.: 319.0   3rd Qu.: 3.000   3rd Qu.:0.00  
##              Max.   :4918.0   Max.   :43.000   Max.   :7.00  
##                                                              
##   emp.var.rate      cons.price.idx  cons.conf.idx      euribor3m    
##  Min.   :-3.40000   Min.   :92.20   Min.   :-50.80   Min.   :0.634  
##  1st Qu.:-1.80000   1st Qu.:93.08   1st Qu.:-42.70   1st Qu.:1.344  
##  Median : 1.10000   Median :93.44   Median :-41.80   Median :4.857  
##  Mean   : 0.08286   Mean   :93.57   Mean   :-40.54   Mean   :3.623  
##  3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.:-36.40   3rd Qu.:4.961  
##  Max.   : 1.40000   Max.   :94.77   Max.   :-26.90   Max.   :5.045  
##                                                                     
##   nr.employed      deposit      
##  Min.   :4964   Min.   :0.0000  
##  1st Qu.:5099   1st Qu.:0.0000  
```

```
##   Median :5191    Median :0.0000
##   Mean   :5167    Mean   :0.1113
##   3rd Qu.:5228    3rd Qu.:0.0000
##   Max.   :5228    Max.   :1.0000
##
```

Split into traning and test dataset

```
set.seed(1)
N <- seq(38245)
S <- sample(N,30596)
bankTrain <- bankDf[S,]
bankTest <- bankDf[-S,]
summary(bankTrain)
```

```
##       age                  job             marital                 educati
on
##   Min.   :17.00   admin.     :7937   divorced: 3427   basic.4y           :3
184
##   1st Qu.:32.00   blue-collar:6856   married :18600   basic.6y           :1
786
##   Median :38.00   technician :5117   single  : 8569   basic.9y           :4
696
##   Mean   :39.86   services   :3001                    high.school        :7
392
##   3rd Qu.:47.00   management :2174                    illiterate         :
14
##   Max.   :98.00   retired    :1249                    professional.course:4
070
##                   (Other)    :4262                    university.degree  :9
454
##   housing   loan      telephone     month       day_of_week   duration
##   0:14180   0:25811   0:19517   may     :10233   fri:5792    Min.   :   0.0
##   1:16416   1: 4785   1:11079   jul     : 5316   mon:6357    1st Qu.: 102.0
##                                 aug     : 4673   thu:6447    Median : 180.0
##                                 jun     : 3876   tue:5954    Mean   : 257.6
##                                 nov     : 3113   wed:6046    3rd Qu.: 320.0
##                                 apr     : 1927               Max.   :4199.0
##                                 (Other): 1458
##      campaign        previous        emp.var.rate      cons.price.idx
##   Min.   : 1.000   Min.   :0.0000   Min.   :-3.40000   Min.   :92.20
##   1st Qu.: 1.000   1st Qu.:0.0000   1st Qu.:-1.80000   1st Qu.:93.08
##   Median : 2.000   Median :0.0000   Median : 1.10000   Median :93.44
##   Mean   : 2.556   Mean   :0.1704   Mean   : 0.08556   Mean   :93.57
##   3rd Qu.: 3.000   3rd Qu.:0.0000   3rd Qu.: 1.40000   3rd Qu.:93.99
##   Max.   :43.000   Max.   :6.0000   Max.   : 1.40000   Max.   :94.77
##
##   cons.conf.idx      euribor3m      nr.employed      deposit
##   Min.   :-50.80   Min.   :0.634   Min.   :4964   Min.   :0.0000
##   1st Qu.:-42.70   1st Qu.:1.344   1st Qu.:5099   1st Qu.:0.0000
##   Median :-41.80   Median :4.857   Median :5191   Median :0.0000
```

```
##  Mean   :-40.53   Mean   :3.625   Mean   :5167   Mean   :0.1105
##  3rd Qu.:-36.40   3rd Qu.:4.961   3rd Qu.:5228   3rd Qu.:0.0000
##  Max.   :-26.90   Max.   :5.045   Max.   :5228   Max.   :1.0000
##
```

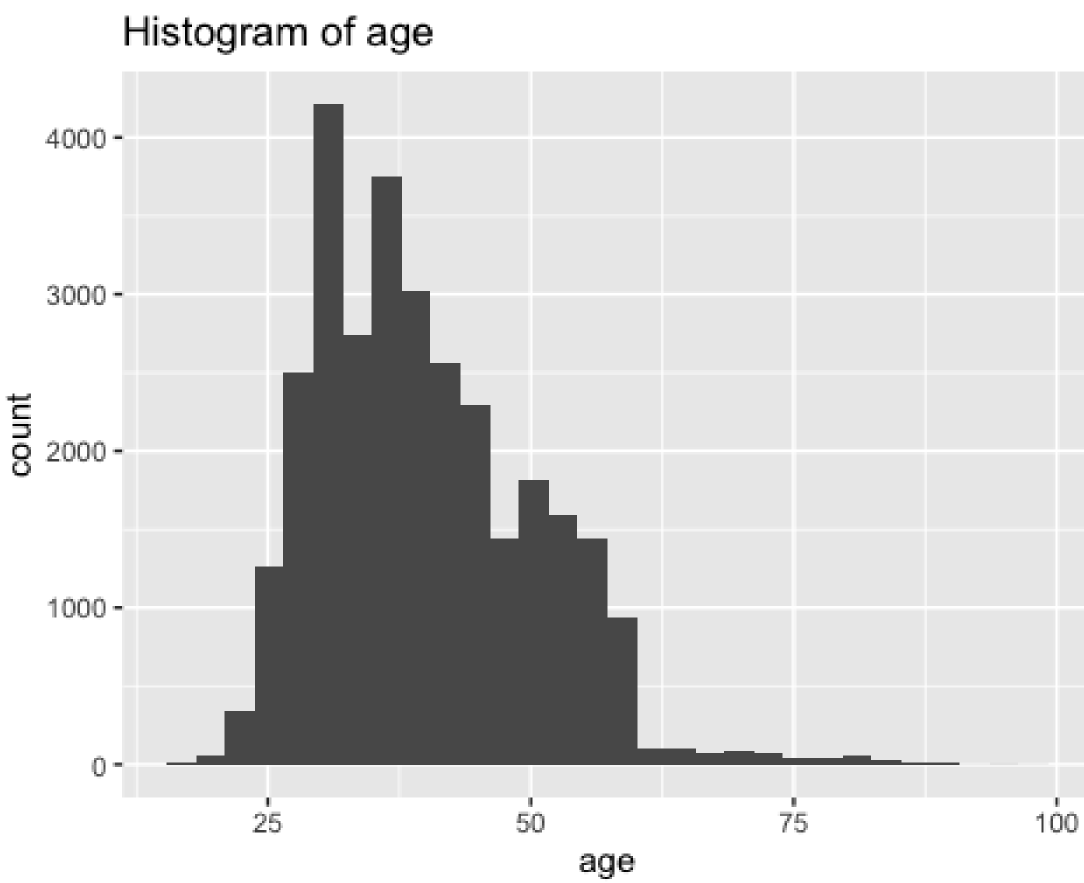
```
summary(bankTest)
```

```
##       age                 job           marital                   educatio
n
##  Min.   :18.00   admin.     :2000   divorced: 875   basic.4y           : 8
18
##  1st Qu.:32.00   blue-collar:1704   married :4583   basic.6y           : 4
18
##  Median :38.00   technician :1263   single  :2191   basic.9y           :11
60
##  Mean   :39.87   services   : 715                   high.school        :18
52
##  3rd Qu.:47.00   management : 554                   illiterate         :
4
##  Max.   :98.00   retired    : 328                   professional.course:10
30
##                  (Other)    :1085                   university.degree  :23
67
##  housing  loan     telephone     month      day_of_week    duration
##  0:3487   0:6475   0:4924    may    :2561   fri:1432    Min.   :   0.0
##  1:4162   1:1174   1:2725    jul    :1314   mon:1570    1st Qu.: 104.0
##                              aug    :1149   thu:1564    Median : 179.0
##                              jun    : 970   tue:1527    Mean   : 260.8
##                              nov    : 785   wed:1556    3rd Qu.: 318.0
##                              apr    : 509               Max.   :4918.0
##                              (Other): 361
##     campaign        previous       emp.var.rate      cons.price.idx
##  Min.   : 1.000   Min.   :0.0000   Min.   :-3.40000   Min.   :92.20
##  1st Qu.: 1.000   1st Qu.:0.0000   1st Qu.:-1.80000   1st Qu.:93.08
##  Median : 2.000   Median :0.0000   Median : 1.10000   Median :93.44
##  Mean   : 2.611   Mean   :0.1685   Mean   : 0.07205   Mean   :93.57
##  3rd Qu.: 3.000   3rd Qu.:0.0000   3rd Qu.: 1.40000   3rd Qu.:93.99
##  Max.   :42.000   Max.   :7.0000   Max.   : 1.40000   Max.   :94.77
##
##  cons.conf.idx      euribor3m      nr.employed      deposit
##  Min.   :-50.80   Min.   :0.634   Min.   :4964   Min.   :0.0000
##  1st Qu.:-42.70   1st Qu.:1.344   1st Qu.:5099   1st Qu.:0.0000
##  Median :-41.80   Median :4.857   Median :5191   Median :0.0000
##  Mean   :-40.59   Mean   :3.616   Mean   :5167   Mean   :0.1145
##  3rd Qu.:-36.40   3rd Qu.:4.961   3rd Qu.:5228   3rd Qu.:0.0000
##  Max.   :-26.90   Max.   :5.045   Max.   :5228   Max.   :1.0000
##
```

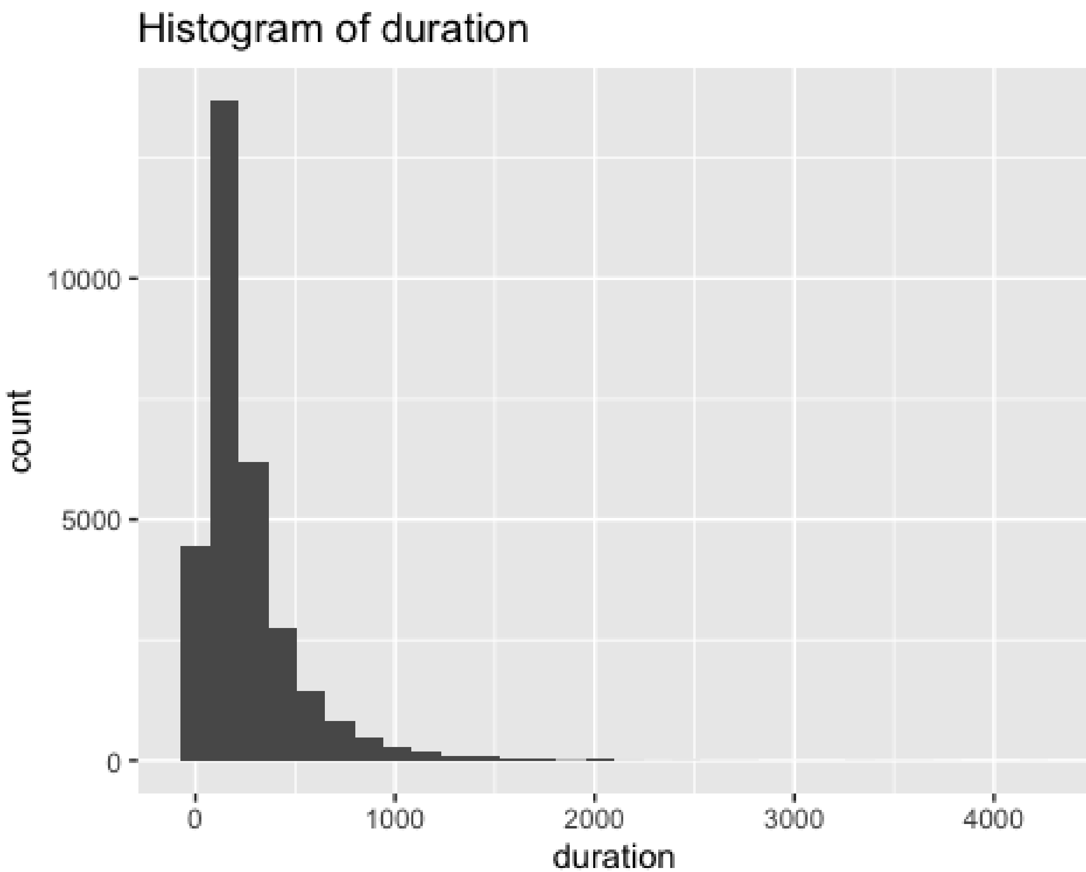
Histogram showing the distribution

Looking at the summary table, a histogram of age, `duration`, `campaign`, `previous` may be worth looking at since the data seems to be skewed and needs some transformation.

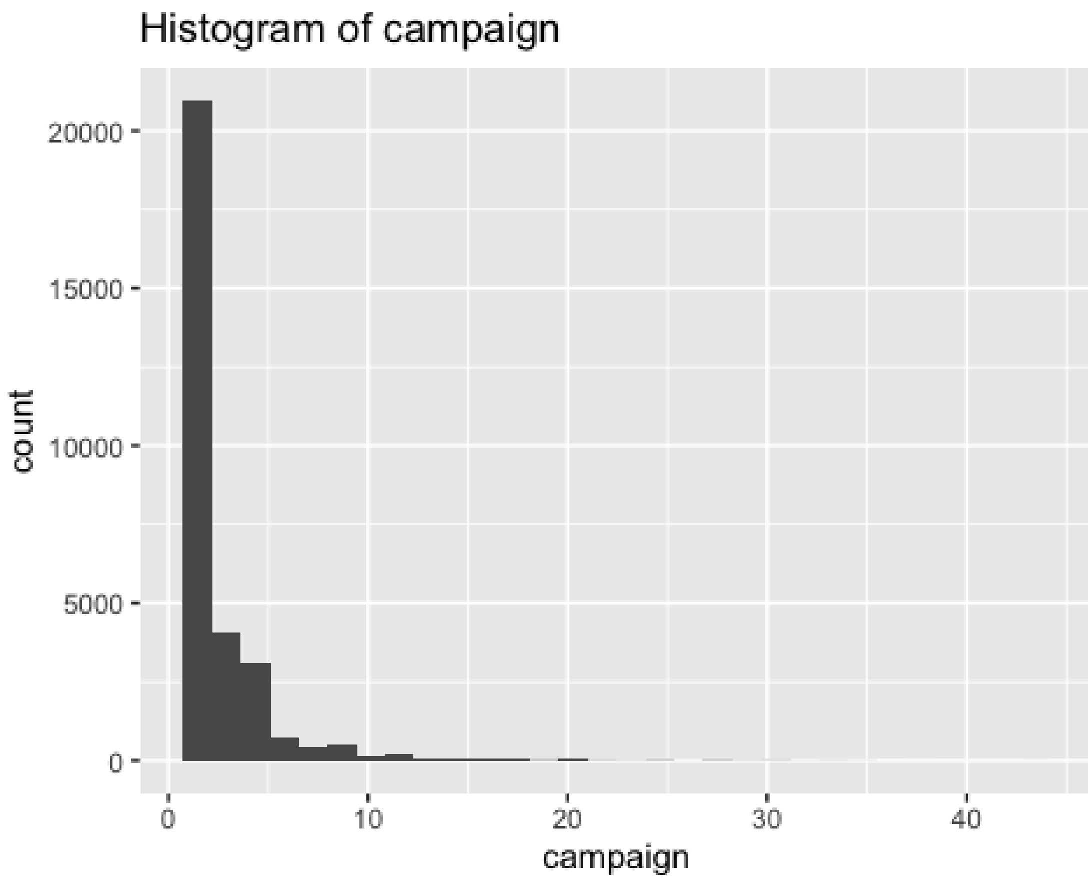
```
bankTrain %>%
  ggplot(aes(age)) + geom_histogram() +
  labs(title = "Histogram of age")

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



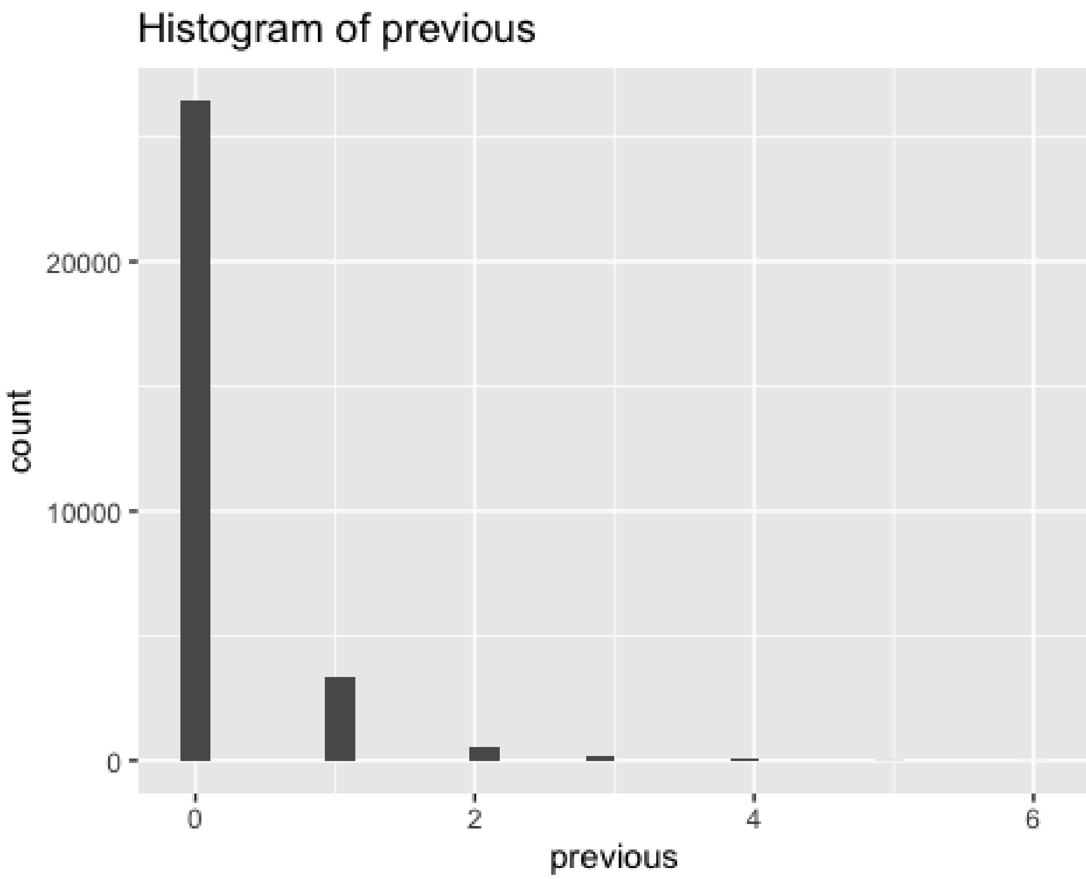

```
bankTrain %>%
  ggplot(aes(duration)) + geom_histogram() +
  labs(title = "Histogram of duration")

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




```
bankTrain %>%
  ggplot(aes(campaign)) + geom_histogram() +
  labs(title = "Histogram of campaign")

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



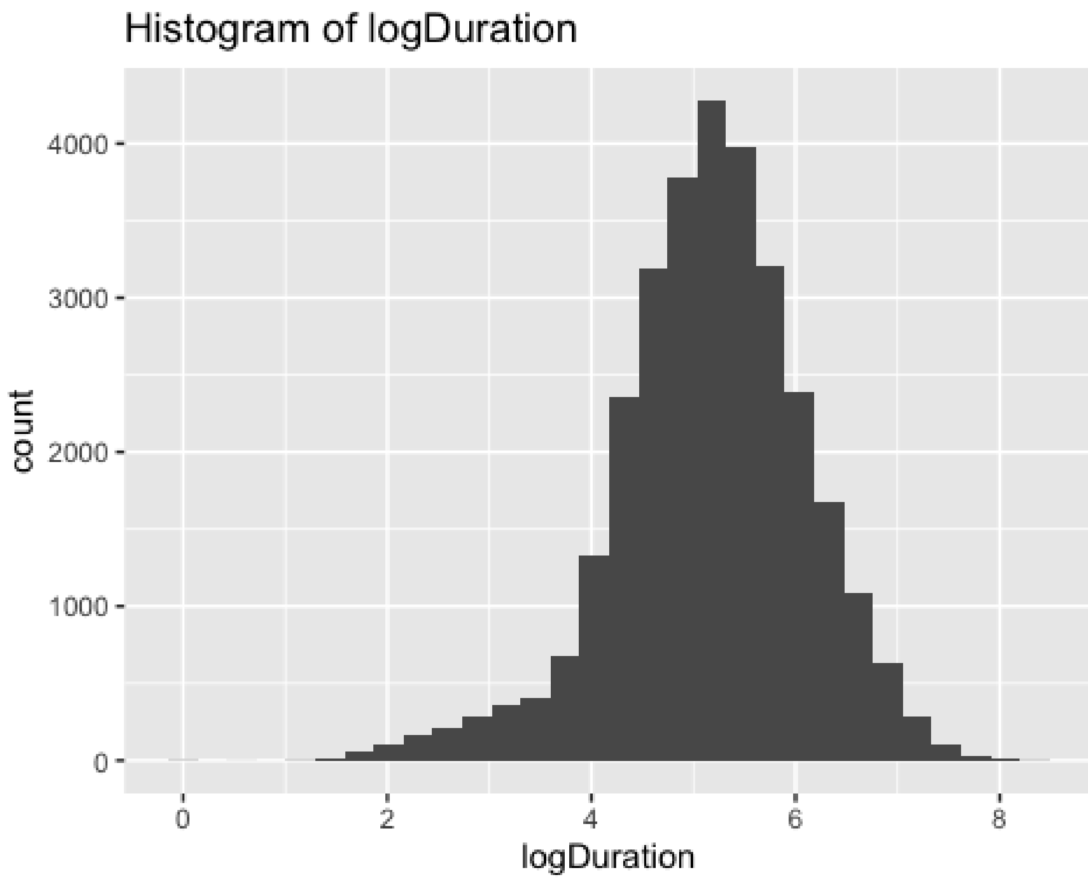

```
bankTrain %>%
  ggplot(aes(previous)) + geom_histogram() +
  labs(title = "Histogram of previous")

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



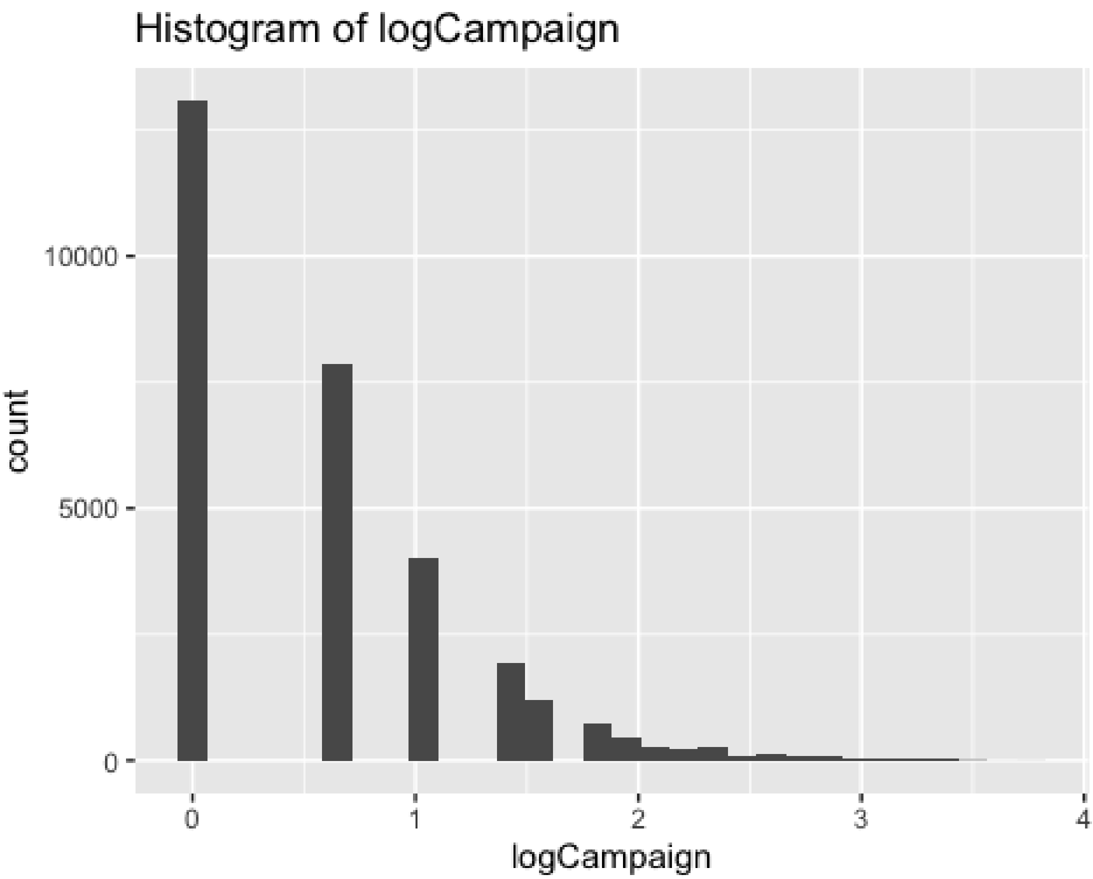

```
table(bankTrain$previous)

##
##     0     1     2     3     4     5     6
## 26451  3386   531   164    50    11     3
```

We will use log transformation on `duration` and `campaign`.

```
#log transformation
bankTrain <- bankTrain %>%
  mutate(logDuration = log(duration))

bankTrain <- bankTrain %>%
  mutate(logCampaign = log(campaign))

bankTrain %>%
  ggplot(aes(logDuration)) + geom_histogram() +
  labs(title = "Histogram of logDuration")

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

## Warning: Removed 2 rows containing non-finite values (stat_bin).
```




```
bankTrain %>%
  ggplot(aes(logCampaign)) + geom_histogram() +
  labs(title = "Histogram of logCampaign")

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



campaign seems to be worsened off so we may leave it alone instead of taking the log transformation.

```
bankTrain <- bankTrain %>%
  select(!logCampaign) %>%
  select(!duration)
```

Modeling process

```
bankTrain <- bankTrain %>%
  filter(logDuration != -Inf)

reg <- glm(deposit ~ ., bankTrain, family = binomial)
summary(reg)

##
## Call:
## glm(formula = deposit ~ ., family = binomial, data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5561  -0.3189  -0.1485  -0.0632   3.7500
##
## Coefficients:
```

```
##                                Estimate Std. Error z value Pr(>|z|)    
## (Intercept)                  -2.530e+02  4.478e+01  -5.651 1.59e-08 ***
## age                          -2.421e-03  2.850e-03  -0.850 0.395576    
## jobblue-collar               -2.300e-01  9.211e-02  -2.497 0.012529 *  
## jobentrepreneur              -1.958e-01  1.453e-01  -1.348 0.177596    
## jobhousemaid                 -1.132e-01  1.708e-01  -0.663 0.507475    
## jobmanagement                -8.614e-03  9.853e-02  -0.087 0.930332    
## jobretired                    4.055e-01  1.268e-01   3.198 0.001383 ** 
## jobself-employed             -1.192e-01  1.356e-01  -0.879 0.379300    
## jobservices                  -2.502e-01  1.006e-01  -2.486 0.012911 *  
## jobstudent                    2.193e-01  1.428e-01   1.536 0.124587    
## jobtechnician                 2.858e-02  8.226e-02   0.347 0.728259    
## jobunemployed                 1.060e-01  1.473e-01   0.719 0.471833    
## maritalmarried               -8.433e-04  7.851e-02  -0.011 0.991430    
## maritalsingle                 4.821e-03  9.012e-02   0.053 0.957341    
## educationbasic.6y             1.770e-01  1.346e-01   1.315 0.188473    
## educationbasic.9y             8.958e-02  1.067e-01   0.840 0.400958    
## educationhigh.school          1.414e-01  1.051e-01   1.345 0.178665    
## educationilliterate           1.181e+00  8.270e-01   1.428 0.153161    
## educationprofessional.course  2.212e-01  1.150e-01   1.923 0.054458 .  
## educationuniversity.degree    2.847e-01  1.060e-01   2.686 0.007236 ** 
## housing1                      1.754e-04  4.763e-02   0.004 0.997062    
## loan1                        -5.632e-02  6.627e-02  -0.850 0.395396    
## telephone1                   -6.686e-01  9.534e-02  -7.012 2.35e-12 ***
## monthaug                      1.193e+00  1.482e-01   8.045 8.60e-16 ***
## monthdec                      4.219e-01  2.532e-01   1.666 0.095679 .  
## monthjul                      3.602e-01  1.144e-01   3.148 0.001643 ** 
## monthjun                     -3.054e-01  1.510e-01  -2.022 0.043135 *  
## monthmar                      2.478e+00  1.800e-01  13.765  < 2e-16 ***
## monthmay                     -3.496e-01  9.853e-02  -3.548 0.000388 ***
## monthnov                     -3.442e-01  1.403e-01  -2.454 0.014145 *  
## monthoct                      4.315e-01  1.804e-01   2.391 0.016794 *  
## monthsep                      8.618e-01  2.126e-01   4.054 5.04e-05 ***
## day_of_weekmon               -9.379e-02  7.695e-02  -1.219 0.222946    
## day_of_weekthu                6.718e-02  7.457e-02   0.901 0.367675    
## day_of_weektue                2.946e-02  7.739e-02   0.381 0.703414    
## day_of_weekwed                1.707e-01  7.610e-02   2.243 0.024916 *  
## campaign                     -2.040e-02  1.329e-02  -1.535 0.124803    
## previous                      1.590e-01  3.948e-02   4.027 5.64e-05 ***
## emp.var.rate                 -2.003e+00  1.709e-01 -11.721  < 2e-16 ***
## cons.price.idx                2.342e+00  2.974e-01   7.878 3.34e-15 ***
## cons.conf.idx                 2.603e-02  9.512e-03   2.737 0.006208 ** 
## euribor3m                     5.835e-01  1.523e-01   3.830 0.000128 ***
## nr.employed                   3.442e-03  3.605e-03   0.955 0.339654    
## logDuration                   2.235e+00  4.037e-02  55.354  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
```

```
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12182  on 30550  degrees of freedom
## AIC: 12270
##
## Number of Fisher Scoring iterations: 7
```

We would remove `age`, `job`, `marital`, `education`, `housing`, `loan`, `day_of_week`, `campaign`, `nr.employed`

```
reg2 <- glm(deposit ~ telephone + month + previous + emp.var.rate + cons.pric
e.idx + cons.conf.idx + euribor3m + logDuration, bankTrain, family = binomial
)
summary(reg2)
```

```
##
## Call:
## glm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##     cons.price.idx + cons.conf.idx + euribor3m + logDuration,
##     family = binomial, data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5786  -0.3211  -0.1504  -0.0651   3.5965
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.180e+02  1.247e+01 -17.482  < 2e-16 ***
## telephone1     -6.623e-01  9.034e-02  -7.332 2.27e-13 ***
## monthaug        1.248e+00  1.325e-01   9.419  < 2e-16 ***
## monthdec        3.976e-01  2.377e-01   1.673 0.094366 .
## monthjul        3.916e-01  1.125e-01   3.482 0.000498 ***
## monthjun       -2.219e-01  1.222e-01  -1.816 0.069418 .
## monthmar        2.465e+00  1.514e-01  16.282  < 2e-16 ***
## monthmay       -4.003e-01  8.953e-02  -4.471 7.77e-06 ***
## monthnov       -3.411e-01  1.252e-01  -2.724 0.006446 **
## monthoct        3.845e-01  1.492e-01   2.577 0.009969 **
## monthsep        8.062e-01  1.612e-01   5.002 5.68e-07 ***
## previous        1.597e-01  3.938e-02   4.055 5.02e-05 ***
## emp.var.rate   -1.957e+00  1.369e-01 -14.303  < 2e-16 ***
## cons.price.idx  2.153e+00  1.291e-01  16.676  < 2e-16 ***
## cons.conf.idx   2.292e-02  6.733e-03   3.405 0.000662 ***
## euribor3m       7.030e-01  1.035e-01   6.794 1.09e-11 ***
## logDuration     2.223e+00  4.009e-02  55.456  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12267  on 30577  degrees of freedom
```

```
## AIC: 12301
##
## Number of Fisher Scoring iterations: 7
```

```
lrm(deposit ~ telephone + month + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + euribor3m + logDuration, bankTrain)
```

```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##      cons.price.idx + cons.conf.idx + euribor3m + logDuration,
##      data = bankTrain)
##
##                         Model Likelihood    Discrimination    Rank Discrim
.
##                               Ratio Test           Indexes          Indexe
s
##  Obs         30594    LR chi2    9005.42    R2       0.509    C       0.93
3
##   0          27212    d.f.            16    g        2.764    Dxy     0.86
6
##   1           3382    Pr(> chi2) <0.0001    gr      15.870    gamma   0.86
6
##  max |deriv| 1e-09                          gp       0.165    tau-a   0.17
0
##                                             Brier    0.063
##
##                   Coef      S.E.    Wald Z Pr(>|Z|)
##  Intercept      -218.0026 12.4701 -17.48 <0.0001
##  telephone=1      -0.6623  0.0903  -7.33 <0.0001
##  month=aug         1.2484  0.1325   9.42 <0.0001
##  month=dec         0.3976  0.2377   1.67 0.0944
##  month=jul         0.3916  0.1125   3.48 0.0005
##  month=jun        -0.2219  0.1222  -1.82 0.0694
##  month=mar         2.4646  0.1514  16.28 <0.0001
##  month=may        -0.4003  0.0895  -4.47 <0.0001
##  month=nov        -0.3411  0.1252  -2.72 0.0064
##  month=oct         0.3845  0.1492   2.58 0.0100
##  month=sep         0.8062  0.1612   5.00 <0.0001
##  previous          0.1597  0.0394   4.05 <0.0001
##  emp.var.rate     -1.9575  0.1369 -14.30 <0.0001
##  cons.price.idx    2.1529  0.1291  16.68 <0.0001
##  cons.conf.idx     0.0229  0.0067   3.40 0.0007
##  euribor3m         0.7030  0.1035   6.79 <0.0001
##  logDuration       2.2232  0.0401  55.46 <0.0001
##
```

We will remove `month` because some of the p-values of its categories aren't statistically significant.

```r
reg3 <- glm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx +
euribor3m + cons.conf.idx + logDuration, bankTrain, family = binomial)
summary(reg3)
```

```
##
## Call:
## glm(formula = deposit ~ telephone + previous + emp.var.rate +
##     cons.price.idx + euribor3m + cons.conf.idx + logDuration,
##     family = binomial, data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1289  -0.3441  -0.1633  -0.0712   3.7512
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.646e+02  7.453e+00 -22.080  < 2e-16 ***
## telephone1     -1.146e+00  7.148e-02 -16.026  < 2e-16 ***
## previous        1.411e-01  3.773e-02   3.739 0.000185 ***
## emp.var.rate   -1.045e+00  7.954e-02 -13.133  < 2e-16 ***
## cons.price.idx  1.647e+00  7.786e-02  21.149  < 2e-16 ***
## euribor3m       3.723e-02  6.222e-02   0.598 0.549589
## cons.conf.idx   9.261e-02  4.803e-03  19.284  < 2e-16 ***
## logDuration     2.124e+00  3.839e-02  55.336  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12803  on 30586  degrees of freedom
## AIC: 12819
##
## Number of Fisher Scoring iterations: 7
```

```r
lrm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx + euribor3
m + cons.conf.idx + logDuration, bankTrain)
```

```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + previous + emp.var.rate +
##      cons.price.idx + euribor3m + cons.conf.idx + logDuration,
##      data = bankTrain)
##
##                        Model Likelihood    Discrimination    Rank Discrim
.
##                              Ratio Test           Indexes           Indexe
s
##  Obs         30594    LR chi2    8469.29    R2       0.483    C       0.92
2
```

```
##   0          27212    d.f.             7    g        2.655    Dxy     0.84
3
##   1           3382    Pr(> chi2) <0.0001    gr      14.231    gamma   0.84
3
##  max |deriv| 1e-09                         gp       0.161    tau-a   0.16
6
##                                            Brier    0.064
##
##                   Coef     S.E.   Wald Z Pr(>|Z|)
##  Intercept      -164.5669 7.4532 -22.08 <0.0001
##  telephone=1      -1.1456 0.0715 -16.03 <0.0001
##  previous          0.1411 0.0377   3.74 0.0002
##  emp.var.rate     -1.0447 0.0795 -13.13 <0.0001
##  cons.price.idx    1.6467 0.0779  21.15 <0.0001
##  euribor3m         0.0372 0.0622   0.60 0.5496
##  cons.conf.idx     0.0926 0.0048  19.28 <0.0001
##  logDuration       2.1243 0.0384  55.34 <0.0001
##
```

Also, remove euribor3m.

```
reg4 <- glm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + logDuration, bankTrain, family = binomial)
summary(reg4)
```

```
##
## Call:
## glm(formula = deposit ~ telephone + previous + emp.var.rate +
##     cons.price.idx + cons.conf.idx + logDuration, family = binomial,
##     data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1344  -0.3443  -0.1632  -0.0712   3.7661
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.618e+02  5.781e+00 -27.982  < 2e-16 ***
## telephone1     -1.134e+00  6.899e-02 -16.444  < 2e-16 ***
## previous        1.376e-01  3.729e-02   3.691 0.000223 ***
## emp.var.rate   -9.994e-01  2.418e-02 -41.330  < 2e-16 ***
## cons.price.idx  1.619e+00  6.193e-02  26.134  < 2e-16 ***
## cons.conf.idx   9.366e-02  4.468e-03  20.963  < 2e-16 ***
## logDuration     2.124e+00  3.838e-02  55.336  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
```

```
## Residual deviance: 12803  on 30587  degrees of freedom
## AIC: 12817
##
## Number of Fisher Scoring iterations: 7
```

```
lrm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx + cons.con
f.idx + logDuration, bankTrain)
```

```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + previous + emp.var.rate +
##      cons.price.idx + cons.conf.idx + logDuration, data = bankTrain)
##
##                         Model Likelihood    Discrimination    Rank Discrim
.
##                               Ratio Test           Indexes          Indexe
s
##  Obs          30594    LR chi2    8468.93    R2       0.483    C       0.92
2
##   0           27212    d.f.             6    g        2.655    Dxy     0.84
3
##   1            3382    Pr(> chi2) <0.0001    gr      14.221    gamma   0.84
3
##  max |deriv| 2e-09                           gp       0.161    tau-a   0.16
6
##                                              Brier    0.064
##
##                Coef      S.E.   Wald Z Pr(>|Z|)
##  Intercept      -161.7572 5.7807 -27.98 <0.0001
##  telephone=1      -1.1345 0.0690 -16.44 <0.0001
##  previous          0.1376 0.0373   3.69 0.0002
##  emp.var.rate     -0.9994 0.0242 -41.33 <0.0001
##  cons.price.idx    1.6185 0.0619  26.13 <0.0001
##  cons.conf.idx     0.0937 0.0045  20.96 <0.0001
##  logDuration       2.1239 0.0384  55.34 <0.0001
##
```

```
# Drop-in deviance tests

pchisq(21272-12182,43,lower.tail = FALSE)
```

```
## [1] 0
```

```
pchisq(21272-12267,16,lower.tail = FALSE)
```

```
## [1] 0
```

```
pchisq(21272-12803,7,lower.tail = FALSE)
```

```
## [1] 0
```

```
pchisq(21272-12803,6,lower.tail = FALSE)
```

```
## [1] 0
```

We will have to now consider moving forward with one of the models. We should definitely eliminate model 1 as it has too many varriables with statistically insignificant p-values. We should also eliminate model 3 because `euribor3m` has a statistically insignificant p-values. We are left with model 2 and 4. The drop-in deviance tests yield 0 for all models, indicating that the probability of getting a larger or equal drop-in deviance is also statistically significant (lower than 0.05). This indicates that it's hard to have a larger or equal drop-in deviance. Thus, our models are adequate. They are significantly better than the null model, explaining a larger amount of variation of `deposit`.

Since the drop-in deviance test doesn't point out which model is better, we will take a look at the residual deviance, and the Dxy.

```
lrm(deposit ~ telephone + month + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + euribor3m + logDuration, bankTrain)

## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##      cons.price.idx + cons.conf.idx + euribor3m + logDuration,
##      data = bankTrain)
##
##                        Model Likelihood    Discrimination    Rank Discrim
.
##                              Ratio Test           Indexes          Indexe
s
##  Obs          30594    LR chi2    9005.42    R2       0.509    C       0.93
3
##   0           27212    d.f.            16    g        2.764    Dxy     0.86
6
##   1            3382    Pr(> chi2) <0.0001    gr      15.870    gamma   0.86
6
##  max |deriv| 1e-09                           gp       0.165    tau-a   0.17
0
##                                              Brier    0.063
##
##                 Coef      S.E.    Wald Z Pr(>|Z|)
##  Intercept      -218.0026 12.4701 -17.48 <0.0001
##  telephone=1      -0.6623  0.0903  -7.33 <0.0001
##  month=aug         1.2484  0.1325   9.42 <0.0001
##  month=dec         0.3976  0.2377   1.67 0.0944
##  month=jul         0.3916  0.1125   3.48 0.0005
##  month=jun        -0.2219  0.1222  -1.82 0.0694
##  month=mar         2.4646  0.1514  16.28 <0.0001
##  month=may        -0.4003  0.0895  -4.47 <0.0001
##  month=nov        -0.3411  0.1252  -2.72 0.0064
##  month=oct         0.3845  0.1492   2.58 0.0100
##  month=sep         0.8062  0.1612   5.00 <0.0001
##  previous          0.1597  0.0394   4.05 <0.0001
```

```
##   emp.var.rate     -1.9575  0.1369 -14.30 <0.0001
##   cons.price.idx    2.1529  0.1291  16.68 <0.0001
##   cons.conf.idx     0.0229  0.0067   3.40 0.0007
##   euribor3m         0.7030  0.1035   6.79 <0.0001
##   logDuration       2.2232  0.0401  55.46 <0.0001
##
```

```
lrm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx + cons.con
f.idx + logDuration, bankTrain)
```

```
## Logistic Regression Model
##
##   lrm(formula = deposit ~ telephone + previous + emp.var.rate +
##       cons.price.idx + cons.conf.idx + logDuration, data = bankTrain)
##
##                         Model Likelihood    Discrimination    Rank Discrim
.
##                               Ratio Test           Indexes           Indexe
s
##   Obs          30594    LR chi2    8468.93    R2       0.483    C       0.92
2
##    0           27212    d.f.             6    g        2.655    Dxy     0.84
3
##    1            3382    Pr(> chi2) <0.0001    gr      14.221    gamma   0.84
3
##   max |deriv| 2e-09                           gp       0.161    tau-a   0.16
6
##                                               Brier    0.064
##
##                  Coef      S.E.   Wald Z Pr(>|Z|)
##   Intercept      -161.7572 5.7807 -27.98 <0.0001
##   telephone=1      -1.1345 0.0690 -16.44 <0.0001
##   previous          0.1376 0.0373   3.69 0.0002
##   emp.var.rate     -0.9994 0.0242 -41.33 <0.0001
##   cons.price.idx    1.6185 0.0619  26.13 <0.0001
##   cons.conf.idx     0.0937 0.0045  20.96 <0.0001
##   logDuration       2.1239 0.0384  55.34 <0.0001
##
```

Clearly, model 2 has a smaller residual deviance (12267) compared to model 4 (12803). Model 2 also has a larger Dxy than model 4, 0.866 compared to 0.843. This means that model 2 fits the data more than model 4, and the variables in model 2 are more significant. The only concern we have is that some of the month is not significant. We may convert month into different Bernoulli variables and eliminate those that are not significant or we may run a drop-in deviance test for month to see if it offers a greater model than the null model.

```
# Drop-in deviance test for month
pchisq(12803-12267,16-7,lower.tail = FALSE)
```

```
## [1] 1.115819e-109
```

It appears that month is quite significant since the drop-in test yields 1.11*10^{-109} as the p-value. After some experiment, we realize that using august as the baseline would make all the p-values significant. This can happen due to the fact that the `monthaug` may affect `deposit` different from other months a lot.

```
bankTrain$month <- relevel(bankTrain$month, ref = "aug")
reg5 <- glm(deposit ~ telephone + month + previous + emp.var.rate + cons.pric
e.idx + cons.conf.idx + euribor3m + logDuration, bankTrain, family = binomial
)
summary(reg5)

##
## Call:
## glm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##     cons.price.idx + cons.conf.idx + euribor3m + logDuration,
##     family = binomial, data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5786  -0.3211  -0.1504  -0.0651   3.5965
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.168e+02  1.242e+01 -17.447  < 2e-16 ***
## telephone1     -6.623e-01  9.034e-02  -7.332 2.27e-13 ***
## monthapr       -1.248e+00  1.325e-01  -9.419  < 2e-16 ***
## monthdec       -8.508e-01  2.381e-01  -3.574 0.000352 ***
## monthjul       -8.568e-01  1.180e-01  -7.258 3.92e-13 ***
## monthjun       -1.470e+00  1.599e-01  -9.196  < 2e-16 ***
## monthmar        1.216e+00  1.551e-01   7.841 4.48e-15 ***
## monthmay       -1.649e+00  1.089e-01 -15.145  < 2e-16 ***
## monthnov       -1.590e+00  1.446e-01 -10.996  < 2e-16 ***
## monthoct       -8.639e-01  1.584e-01  -5.453 4.96e-08 ***
## monthsep       -4.422e-01  1.532e-01  -2.886 0.003900 **
## previous        1.597e-01  3.938e-02   4.055 5.02e-05 ***
## emp.var.rate   -1.957e+00  1.369e-01 -14.303  < 2e-16 ***
## cons.price.idx  2.153e+00  1.291e-01  16.676  < 2e-16 ***
## cons.conf.idx   2.292e-02  6.733e-03   3.405 0.000662 ***
## euribor3m       7.030e-01  1.035e-01   6.794 1.09e-11 ***
## logDuration     2.223e+00  4.009e-02  55.456  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12267  on 30577  degrees of freedom
## AIC: 12301
```

```
##
## Number of Fisher Scoring iterations: 7
```

```
lrm(deposit ~ telephone + month + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + euribor3m + logDuration, bankTrain)
```

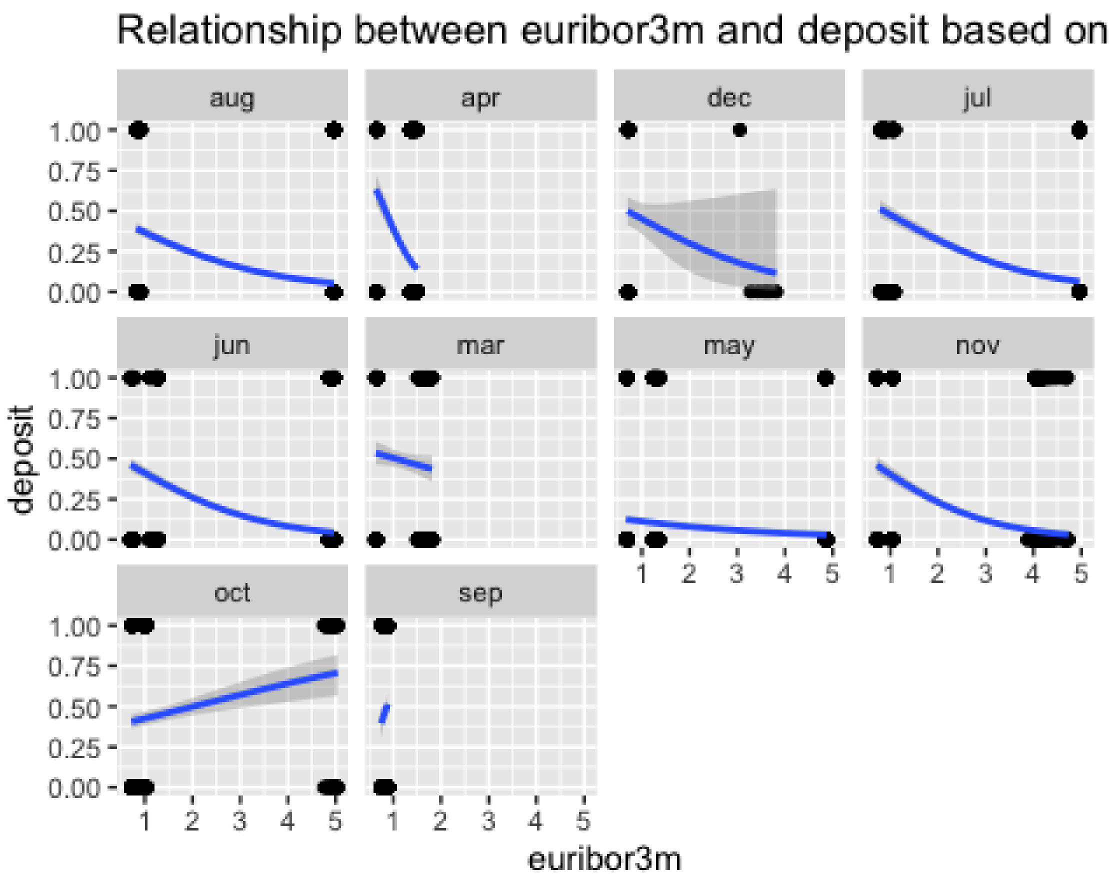
```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##      cons.price.idx + cons.conf.idx + euribor3m + logDuration,
##      data = bankTrain)
##
##                         Model Likelihood    Discrimination    Rank Discrim
.
##                               Ratio Test           Indexes          Indexe
s
##  Obs         30594    LR chi2    9005.42    R2       0.509    C       0.93
3
##   0          27212    d.f.            16    g        2.764    Dxy     0.86
6
##   1           3382    Pr(> chi2) <0.0001    gr      15.870    gamma   0.86
6
##  max |deriv| 1e-09                          gp       0.165    tau-a   0.17
0
##                                             Brier    0.063
##
##                 Coef      S.E.    Wald Z Pr(>|Z|)
##  Intercept      -216.7542 12.4238 -17.45 <0.0001
##  telephone=1      -0.6623  0.0903  -7.33 <0.0001
##  month=apr        -1.2484  0.1325  -9.42 <0.0001
##  month=dec        -0.8508  0.2381  -3.57 0.0004
##  month=jul        -0.8568  0.1180  -7.26 <0.0001
##  month=jun        -1.4703  0.1599  -9.20 <0.0001
##  month=mar         1.2161  0.1551   7.84 <0.0001
##  month=may        -1.6488  0.1089 -15.15 <0.0001
##  month=nov        -1.5895  0.1445 -11.00 <0.0001
##  month=oct        -0.8639  0.1584  -5.45 <0.0001
##  month=sep        -0.4422  0.1532  -2.89 0.0039
##  previous          0.1597  0.0394   4.05 <0.0001
##  emp.var.rate     -1.9575  0.1369 -14.30 <0.0001
##  cons.price.idx    2.1529  0.1291  16.68 <0.0001
##  cons.conf.idx     0.0229  0.0067   3.40 0.0007
##  euribor3m         0.7030  0.1035   6.79 <0.0001
##  logDuration       2.2232  0.0401  55.46 <0.0001
##
```

We will move forward with model 2 and try to improve the model by adding interaction terms.

Interaction Terms

Since when we remove month, euribor3m is also affected a lot, we will try an interaction term between month and euribor3m.

```
bankTrain %>%
  ggplot(aes(euribor3m, deposit)) + geom_point() +
  stat_smooth(method = "glm",method.args = list(family= "binomial")) +
  facet_wrap(~month) +
  labs(title = "Relationship between euribor3m and deposit based on month")

## `geom_smooth()` using formula 'y ~ x'
```




```
reg6 <- glm(deposit ~ telephone + month + previous + emp.var.rate + cons.pric
e.idx + cons.conf.idx + euribor3m + logDuration + month*euribor3m, bankTrain,
family = binomial)
summary(reg6)

##
## Call:
## glm(formula = deposit ~ telephone + month + previous + emp.var.rate +
##     cons.price.idx + cons.conf.idx + euribor3m + logDuration +
##     month * euribor3m, family = binomial, data = bankTrain)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.0986  -0.3117  -0.1434  -0.0614   3.5207
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -194.43155   19.41146 -10.016  < 2e-16 ***
## telephone1           -0.49594    0.10055  -4.932 8.12e-07 ***
## monthapr              0.96046    0.49553   1.938 0.052594 .
## monthdec             -1.93622    0.47475  -4.078 4.53e-05 ***
## monthjul             -0.46212    0.23329  -1.981 0.047611 *
## monthjun             -0.27596    0.25487  -1.083 0.278927
## monthmar             -0.71979    0.40586  -1.774 0.076145 .
## monthmay             -0.53290    0.22848  -2.332 0.019684 *
## monthnov             -0.86790    0.24884  -3.488 0.000487 ***
## monthoct             -1.71380    0.20999  -8.161 3.31e-16 ***
## monthsep             -5.56421    2.51206  -2.215 0.026760 *
## previous              0.16019    0.03967   4.038 5.39e-05 ***
## emp.var.rate         -1.52489    0.23337  -6.534 6.39e-11 ***
## cons.price.idx        1.94062    0.20144   9.634  < 2e-16 ***
## cons.conf.idx         0.07708    0.01183   6.515 7.28e-11 ***
## euribor3m             0.43797    0.19249   2.275 0.022885 *
## logDuration           2.27451    0.04097  55.511  < 2e-16 ***
## monthapr:euribor3m   -1.08968    0.40155  -2.714 0.006654 **
## monthdec:euribor3m    1.91503    0.50571   3.787 0.000153 ***
## monthjul:euribor3m   -0.01630    0.05112  -0.319 0.749770
## monthjun:euribor3m   -0.22983    0.05471  -4.201 2.66e-05 ***
## monthmar:euribor3m    2.17512    0.35015   6.212 5.23e-10 ***
## monthmay:euribor3m   -0.28014    0.07477  -3.747 0.000179 ***
## monthnov:euribor3m   -0.06484    0.06480  -1.001 0.317035
## monthoct:euribor3m    1.10094    0.14615   7.533 4.96e-14 ***
## monthsep:euribor3m    6.33062    2.99808   2.112 0.034724 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12031  on 30568  degrees of freedom
## AIC: 12083
##
## Number of Fisher Scoring iterations: 7
```

```
lrm(deposit ~ telephone + month + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + euribor3m + logDuration + month*euribor3m + campaign, bankTra
in, maxit=1000)
```

```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + month + previous + emp.var.rate +
```

```
##      cons.price.idx + cons.conf.idx + euribor3m + logDuration +
##      month * euribor3m + campaign, data = bankTrain, maxit = 1000)
##
##                        Model Likelihood    Discrimination    Rank Discrim
.
##                              Ratio Test           Indexes          Indexe
s
##  Obs          30594    LR chi2    9244.03    R2       0.520    C       0.93
6
##   0           27212    d.f.            26    g        2.845    Dxy     0.87
2
##   1            3382    Pr(> chi2) <0.0001    gr      17.202    gamma   0.87
2
##  max |deriv| 3e-09                           gp       0.166    tau-a   0.17
1
##                                              Brier    0.061
##
##                        Coef      S.E.    Wald Z Pr(>|Z|)
##  Intercept             -194.0849 19.4093 -10.00 <0.0001
##  telephone=1             -0.4820  0.1009  -4.77 <0.0001
##  month=apr               0.9683  0.4961   1.95 0.0509
##  month=dec              -1.9110  0.4752  -4.02 <0.0001
##  month=jul              -0.4505  0.2335  -1.93 0.0537
##  month=jun              -0.2720  0.2549  -1.07 0.2858
##  month=mar              -0.7321  0.4061  -1.80 0.0714
##  month=may              -0.5236  0.2285  -2.29 0.0219
##  month=nov              -0.8586  0.2490  -3.45 0.0006
##  month=oct              -1.7078  0.2101  -8.13 <0.0001
##  month=sep              -5.5972  2.5127  -2.23 0.0259
##  previous                0.1596  0.0397   4.02 <0.0001
##  emp.var.rate           -1.5179  0.2334  -6.50 <0.0001
##  cons.price.idx          1.9374  0.2014   9.62 <0.0001
##  cons.conf.idx           0.0772  0.0118   6.52 <0.0001
##  euribor3m               0.4369  0.1925   2.27 0.0232
##  logDuration             2.2770  0.0410  55.49 <0.0001
##  campaign               -0.0238  0.0135  -1.76 0.0777
##  month=apr * euribor3m  -1.0970  0.4019  -2.73 0.0063
##  month=dec * euribor3m   1.8950  0.5061   3.74 0.0002
##  month=jul * euribor3m  -0.0179  0.0511  -0.35 0.7265
##  month=jun * euribor3m  -0.2319  0.0547  -4.24 <0.0001
##  month=mar * euribor3m   2.1917  0.3504   6.25 <0.0001
##  month=may * euribor3m  -0.2856  0.0748  -3.82 0.0001
##  month=nov * euribor3m  -0.0699  0.0649  -1.08 0.2816
##  month=oct * euribor3m   1.0920  0.1463   7.46 <0.0001
##  month=sep * euribor3m   6.3707  2.9988   2.12 0.0336
##
```

Most p-values are statistically significant (< 0.05), and Dxy increases from 0.866 to 0.872 so we would move forward with this model.

Adding one more variable

Looking back at the first model, we realize that higher education (professional.course and university.degree) is actually quite significant. We would try to create a dummy variable for higher education

```
table(bankTrain$education)

## 
##            basic.4y            basic.6y            basic.9y         high.s
chool 
##                3184                1786                4695               
7392 
##          illiterate professional.course   university.degree 
##                  14                4070                9453

bankTrain <- bankTrain %>%
  mutate(higherEd = ifelse(education == "professional.course" | education ==
"university.degree", 1 ,0))

reg6 <- glm(deposit ~ telephone + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + logDuration + month*euribor3m + higherEd, bankTrain, family =
binomial)
summary(reg6)

## 
## Call:
## glm(formula = deposit ~ telephone + previous + emp.var.rate + 
##     cons.price.idx + cons.conf.idx + logDuration + month * euribor3m + 
##     higherEd, family = binomial, data = bankTrain)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -4.1241  -0.3106  -0.1434  -0.0606   3.4987  
## 
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)    
## (Intercept)        -1.926e+02  1.942e+01  -9.914  < 2e-16 ***
## telephone1         -4.998e-01  1.006e-01  -4.968 6.78e-07 ***
## previous            1.606e-01  3.971e-02   4.045 5.24e-05 ***
## emp.var.rate       -1.506e+00  2.334e-01  -6.451 1.11e-10 ***
## cons.price.idx      1.920e+00  2.016e-01   9.522  < 2e-16 ***
## cons.conf.idx       7.659e-02  1.184e-02   6.471 9.74e-11 ***
## logDuration         2.278e+00  4.103e-02  55.523  < 2e-16 ***
## monthapr            9.520e-01  4.959e-01   1.920 0.054884 .  
## monthdec           -1.909e+00  4.776e-01  -3.997 6.42e-05 ***
## monthjul           -4.581e-01  2.331e-01  -1.966 0.049351 *  
## monthjun           -2.874e-01  2.547e-01  -1.128 0.259281    
## monthmar           -7.295e-01  4.060e-01  -1.797 0.072347 .  
## monthmay           -5.148e-01  2.286e-01  -2.252 0.024325 *  
```

```
## monthnov           -8.559e-01  2.489e-01  -3.439 0.000585 ***
## monthoct           -1.697e+00  2.101e-01  -8.076 6.70e-16 ***
## monthsep           -5.287e+00  2.519e+00  -2.099 0.035806 *
## euribor3m           4.183e-01  1.925e-01   2.173 0.029756 *
## higherEd            1.903e-01  4.867e-02   3.911 9.20e-05 ***
## monthapr:euribor3m -1.067e+00  4.019e-01  -2.655 0.007932 **
## monthdec:euribor3m  1.899e+00  5.104e-01   3.721 0.000199 ***
## monthjul:euribor3m -4.836e-03  5.116e-02  -0.095 0.924686
## monthjun:euribor3m -2.111e-01  5.493e-02  -3.843 0.000122 ***
## monthmar:euribor3m  2.174e+00  3.502e-01   6.208 5.35e-10 ***
## monthmay:euribor3m -2.673e-01  7.488e-02  -3.570 0.000357 ***
## monthnov:euribor3m -6.019e-02  6.483e-02  -0.928 0.353176
## monthoct:euribor3m  1.112e+00  1.461e-01   7.610 2.75e-14 ***
## monthsep:euribor3m  6.002e+00  3.005e+00   1.997 0.045817 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12016  on 30567  degrees of freedom
## AIC: 12070
##
## Number of Fisher Scoring iterations: 7
```

```
lrm <- lrm(deposit ~ telephone  + previous + emp.var.rate + cons.price.idx +
cons.conf.idx + logDuration + month*euribor3m + higherEd, bankTrain, maxit =
1000)
```

Most p-values are statistically significant (lower than 0.05), and Dxy increases from 0.872 to 0.873 so we will decide on using this model

```
summary(reg6)

##
## Call:
## glm(formula = deposit ~ telephone + previous + emp.var.rate +
##     cons.price.idx + cons.conf.idx + logDuration + month * euribor3m +
##     higherEd, family = binomial, data = bankTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.1241  -0.3106  -0.1434  -0.0606   3.4987
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -1.926e+02  1.942e+01  -9.914  < 2e-16 ***
## telephone1         -4.998e-01  1.006e-01  -4.968 6.78e-07 ***
## previous            1.606e-01  3.971e-02   4.045 5.24e-05 ***
## emp.var.rate       -1.506e+00  2.334e-01  -6.451 1.11e-10 ***
## cons.price.idx      1.920e+00  2.016e-01   9.522  < 2e-16 ***
```

```
## cons.conf.idx       7.659e-02  1.184e-02   6.471 9.74e-11 ***
## logDuration         2.278e+00  4.103e-02  55.523  < 2e-16 ***
## monthapr            9.520e-01  4.959e-01   1.920 0.054884 .
## monthdec           -1.909e+00  4.776e-01  -3.997 6.42e-05 ***
## monthjul           -4.581e-01  2.331e-01  -1.966 0.049351 *
## monthjun           -2.874e-01  2.547e-01  -1.128 0.259281
## monthmar           -7.295e-01  4.060e-01  -1.797 0.072347 .
## monthmay           -5.148e-01  2.286e-01  -2.252 0.024325 *
## monthnov           -8.559e-01  2.489e-01  -3.439 0.000585 ***
## monthoct           -1.697e+00  2.101e-01  -8.076 6.70e-16 ***
## monthsep           -5.287e+00  2.519e+00  -2.099 0.035806 *
## euribor3m           4.183e-01  1.925e-01   2.173 0.029756 *
## higherEd            1.903e-01  4.867e-02   3.911 9.20e-05 ***
## monthapr:euribor3m -1.067e+00  4.019e-01  -2.655 0.007932 **
## monthdec:euribor3m  1.899e+00  5.104e-01   3.721 0.000199 ***
## monthjul:euribor3m -4.836e-03  5.116e-02  -0.095 0.924686
## monthjun:euribor3m -2.111e-01  5.493e-02  -3.843 0.000122 ***
## monthmar:euribor3m  2.174e+00  3.502e-01   6.208 5.35e-10 ***
## monthmay:euribor3m -2.673e-01  7.488e-02  -3.570 0.000357 ***
## monthnov:euribor3m -6.019e-02  6.483e-02  -0.928 0.353176
## monthoct:euribor3m  1.112e+00  1.461e-01   7.610 2.75e-14 ***
## monthsep:euribor3m  6.002e+00  3.005e+00   1.997 0.045817 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 21272  on 30593  degrees of freedom
## Residual deviance: 12016  on 30567  degrees of freedom
## AIC: 12070
##
## Number of Fisher Scoring iterations: 7
```

```
lrm
```

```
## Logistic Regression Model
##
##  lrm(formula = deposit ~ telephone + previous + emp.var.rate +
##      cons.price.idx + cons.conf.idx + logDuration + month * euribor3m +
##      higherEd, data = bankTrain, maxit = 1000)
##
##                        Model Likelihood    Discrimination    Rank Discrim
.
##                              Ratio Test           Indexes           Indexe
s
##  Obs          30594    LR chi2    9256.08    R2       0.521    C       0.93
6
##   0           27212    d.f.            26    g        2.838    Dxy     0.87
3
##   1            3382    Pr(> chi2) <0.0001    gr      17.079    gamma   0.87
```

```
3
##  max |deriv| 8e-10                          gp       0.166    tau-a   0.17
2
##                                             Brier    0.061
##
##                         Coef      S.E.    Wald Z Pr(>|Z|)
##  Intercept             -192.5782 19.4250 -9.91  <0.0001
##  telephone=1             -0.4998  0.1006 -4.97  <0.0001
##  previous                 0.1606  0.0397  4.04  <0.0001
##  emp.var.rate            -1.5057  0.2334 -6.45  <0.0001
##  cons.price.idx           1.9197  0.2016  9.52  <0.0001
##  cons.conf.idx            0.0766  0.0118  6.47  <0.0001
##  logDuration              2.2783  0.0410 55.52  <0.0001
##  month=apr                0.9520  0.4959  1.92  0.0549
##  month=dec               -1.9087  0.4776 -4.00  <0.0001
##  month=jul               -0.4581  0.2331 -1.97  0.0494
##  month=jun               -0.2874  0.2547 -1.13  0.2593
##  month=mar               -0.7295  0.4060 -1.80  0.0723
##  month=may               -0.5148  0.2286 -2.25  0.0243
##  month=nov               -0.8559  0.2489 -3.44  0.0006
##  month=oct               -1.6968  0.2101 -8.08  <0.0001
##  month=sep               -5.2871  2.5187 -2.10  0.0358
##  euribor3m                0.4183  0.1925  2.17  0.0298
##  higherEd                 0.1904  0.0487  3.91  <0.0001
##  month=apr * euribor3m   -1.0669  0.4019 -2.65  0.0079
##  month=dec * euribor3m    1.8990  0.5104  3.72  0.0002
##  month=jul * euribor3m   -0.0048  0.0512 -0.09  0.9247
##  month=jun * euribor3m   -0.2111  0.0549 -3.84  0.0001
##  month=mar * euribor3m    2.1740  0.3502  6.21  <0.0001
##  month=may * euribor3m   -0.2673  0.0749 -3.57  0.0004
##  month=nov * euribor3m   -0.0602  0.0648 -0.93  0.3532
##  month=oct * euribor3m    1.1122  0.1461  7.61  <0.0001
##  month=sep * euribor3m    6.0021  3.0055  2.00  0.0458
##
```

Interpretation:

According to the logistic regression model, we have:

- When all variables equal 0 and it's August, the log odds of `deposit` is -192.5782, and the probability of the customer subscribing to the term deposit is **3.54*10^(-84),** indicating that the customer will not deposit.

- telephone: A shift from using cell phone to telephone is associated with a decrease in the log odds of `deposit` by 0.4998 units, indicating that if the call method is telephone instead of cell phone, the odds of getting the customers to deposit go down by 1.65 times (or 165%). This makes sense as the dataset also include calls of which customers contact the help center. There will be people who need help and will be frustrated if they don't get what they need immediately but some introduction to a term deposit that they don't care about instead. Using cellphone will also create a sense of personal relationship between the caller and the customer instead of a sense of being a part of just a telemarketing campaign.

- previous: When `previous` increases by 1, the log odds of `deposit` increases by 0.16 units, indicating that the odds of successfully having customers deposit go up by 1.17 times (or 117%). As mention aboved in the variable description, previous means number of contacts performed before this campaign and for this client so the more contacts are performed before, the more experience and familiarity the telemarketing team will possess and hence will persuade the customers better.

- emp.var.rate: When `emp.var.rate` increases by 1, the log odds of `deposit` decreases by -1.5057 units, indicating that the odds of successfully having customers deposit go down by 4.51 times (or 451%). emp.var.rate measures the variation of employment rate. High emp.var.rate indicates an unstable economy.

- cons.price.idx: When `cons.price.idx` increases by 1, the log odds of `deposit` increases by 1.92 units, indicating that the odds of sucessfully having customers deposit go up by 6.82 times (or 682%). Higher `cons.price.idx` means higher inflation rate -> higher nominal interest rate so it makes sense that the higher the `cons.price.idx`, the higher chance the customers want to subscribe to a term deposit.

- cons.conf.idx: When `cons.conf.idx` increases by 1, the log odds of `deposit` increases by 0.0766 units, indicating that the odds of successfully having customers deposit go up by 1.08 times (or 108%). It makes sense that the higher the consumer confidence level is, the higher chance they want to subscribe to a term deposit.

- euribor3m: When `euribo3m` increases by 1, the log odds of `deposit` increases by 0.4183 units, indicating that the odds of successfully having customers deposit go up by 1.52 times (or 152%). `euribor3m` is the average interest rates from a panel of large European banks that are used for lending to one another.

- logDuration: When `logDuration` increases by 1, the log odds of `deposit` increases by 2.2783 units, indicating that the odds of successfully having customers deposit go up by 9.76 times (or 976%). This makes sense since normally, if customers receive a call that they don't care about, they will try to end the call as soon as possible. Longer duration also indicates that the company has more time to persuade the customer to subscribe to the term deposit.

- higherEd: A shift from having high education level to not having high education level is associated with an increase in the log odds of `deposit` by 0.1904 units, indicating that if the customer has university degree or professional courses, the odds of getting the customers to deposit go up by 1.21 times (or 121%).

- month: Of all the months, December, September and October are associated with a decrease in the log odds of `deposit`. This might indicate that customers tend to keep money by themselves or use it at the end of the year.

- C is 0.936. This indicates that 93.6% of pairs of 0 and 1 fit the model (0.5->1 - random guessing).

- Dxy is 0.873. This is a rescale of C to make it range from 0 to 1 instead of 0.5 to 1. 0.873 is still a good number. This model explains about 87.3% of our data.

Validate the model

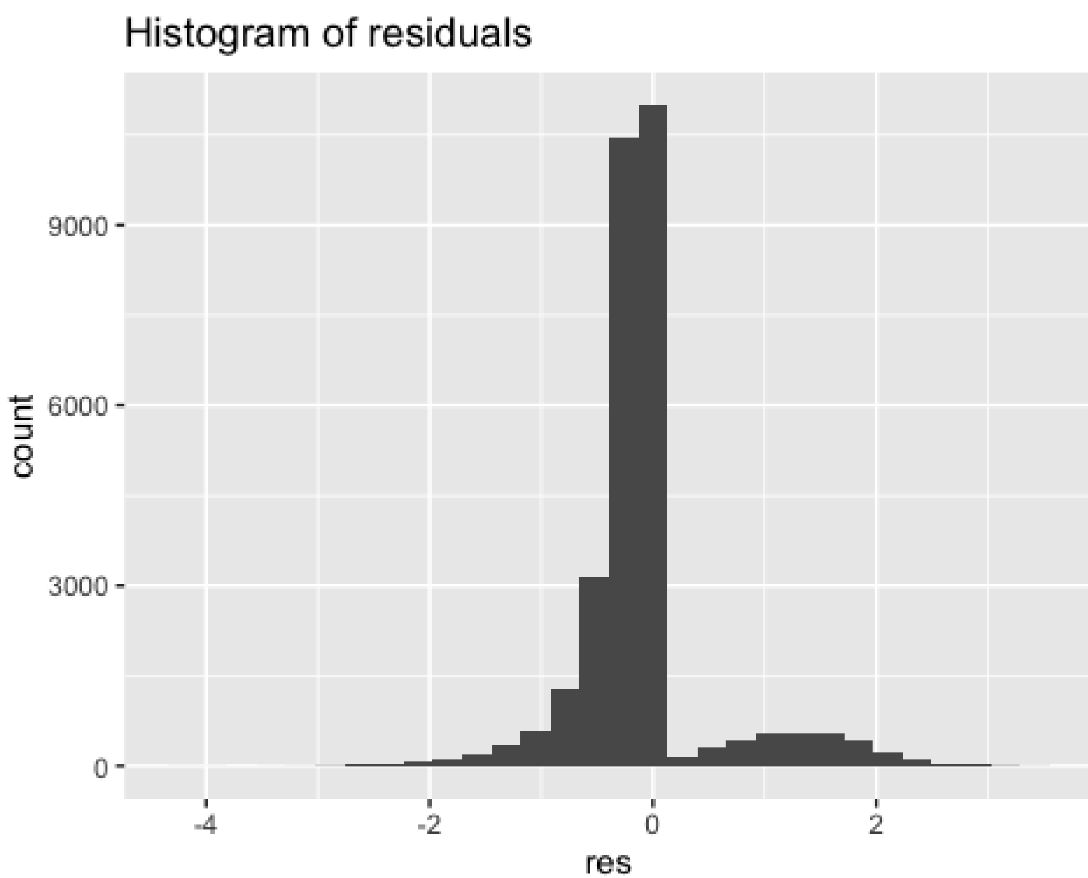
Drop-in deviance test

```
pchisq(21272 - 12016, 27, lower.tail = FALSE)

## [1] 0
```

The drop-in deviance tests yield 0, indicating that the probability of getting a larger or equal drop-in deviance is also statistically significant (lower than 0.05). This indicates that it's hard to have a larger or equal drop-in deviance. Thus, our model is adequate. This is significantly better than the null model, explaining a larger amount of variation of `deposit`.

Check for binormiality and normal distribution

```
bankTrain2 <- bankTrain %>%
  mutate(res = resid(reg6), fit = fitted(reg6))
bankTrain2 %>% ggplot(aes(res)) + geom_histogram() + labs(title = "Histogram
of residuals")

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



The histogram of residual is unbalanced. This may be due to the unbalanced dataset that we have (more 'no' than 'yes' for deposit). However, the distribution still centers at 0 so this is still acceptable. We will also run the Hosmer-Lem test to check for binormiality.

```
hoslem.test(bankTrain2$deposit, bankTrain2$fit,g=3000)

##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  bankTrain2$deposit, bankTrain2$fit
## X-squared = 2891.9, df = 2998, p-value = 0.9159
```

We change the number of bins to 3000 to fit the size of the dataset. The p-value is 0.9159. It is not statistically significant (higher than 0.05) so we fail to reject the null hypothesis that if we break our residuals into bins, each bin has a binormal distribution.

Prediction

Random Prediction

We will start with predicting 3 random observations from the test set

```
bankTest2 <- bankTest %>%
  mutate(logDuration = log(duration)) %>%
  mutate(higherEd = ifelse(education == "professional.course" | education ==
"university.degree", 1 ,0)) %>%
  filter(logDuration != -Inf)

set.seed(4)
N <- seq(7649)
random <- sample(N, 3)
bankTestPt <- bankTest2[random, ]

bankTestPt <- bankTestPt %>%
  mutate(result = 0)
bankTestPt[1, 'result'] <- predict(reg6, bankTestPt[1,], type = "response")
bankTestPt[2, 'result'] <- predict(reg6, bankTestPt[2,], type = "response")
bankTestPt[3, 'result'] <- predict(reg6, bankTestPt[3,], type = "response")
bankTestPt %>%
  dplyr::select(deposit, result)

## # A tibble: 3 × 2
##   deposit result
##     <dbl>  <dbl>
## 1       1 0.271
## 2       0 0.0109
## 3       0 0.0621
```

The result when the actual deposit is 1 is quite higher than the results when the actual deposits are 0 but still not high enough. We will make some calculations to better assess the result.

Recall, Precision, Accuracy

```
bankTest3 <- bankTest2 %>%
  mutate(predict = predict(reg6, bankTest2, type = "response")) %>%
  mutate(predictDeposit = ifelse(predict < 0.5,0,1))

N <- seq(nrow(bankTest3))

for (i in N) {
  if ((bankTest3[i,'predictDeposit'] == 0) && (bankTest3[i, 'deposit'] == 1))
{
    bankTest3[i,'result'] = "FN"
  }
  else if ((bankTest3[i,'predictDeposit'] == 1) && (bankTest3[i, 'deposit'] =
= 1)) {
    bankTest3[i,'result'] = "TP"
  }
  else if ((bankTest3[i,'predictDeposit'] == 1) && (bankTest3[i, 'deposit'] =
= 0)) {
    bankTest3[i,'result'] = "FP"
  }
  else {
    bankTest3[i,'result'] = "TN"
  }
}

FN <- sum(bankTest3$result == "FN")
FP <- sum(bankTest3$result == "FP")
TN <- sum(bankTest3$result == "TN")
TP <- sum(bankTest3$result == "TP")
recall <- TP/(TP + FN)
precision <- TP/(TP + FP)
accuracy <- (TP + TN)/(FP + FN + TP + TN)

recall

## [1] 0.4383562

precision

## [1] 0.6748682

accuracy

## [1] 0.9114685
```

- Recall: From all the customers subscribe to the term deposit, we predict 43.8% of them.

- Precision: From all the customers we predict that they subscribe, 67.4% of them actually do.
- Accuracy: Fromm all predictions, 91.14% is correct.

F. Final Thoughts

1. Some suggestions to the bank in Portugal

- Bank should look at the economy of the country before launching a telemarketing campaign

- They should also train their telemarketing team to handle different type of calls appropriately

- Avoid the end of the year for telemarketing campaigns

- They might also aim their campaign at customers who have higher education levels

2. Future work

- We have an unbalanced dataset => oversampling undersampling methods to get more reliable results

- Analyze whether or not we can apply this model to other similiar-size banks in Portugal