Bank Marketing

This dataset consists of direct marketing campaigns by a Portuguese banking institution using phone calls. The campaigns aimed to sell subscriptions to a bank term deposit (see variable `y`).

Not sure where to begin? Scroll to the bottom to find challenges!

```
suppressPackageStartupMessages(library(tidyverse)) #load data
bank = read_delim('data/bank-marketing.csv', delim=";", show_col_types = FALSE)
nrow(bank)
head(bank, n = 100)
```

41188

		job		education				c.		da...
1	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
2	57	services	married	high.school	unkno...	no	no	telephone	may	mon
3	37	services	married	high.school	no	yes	no	telephone	may	mon
4	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
5	56	services	married	high.school	no	no	yes	telephone	may	mon
6	45	services	married	basic.9y	unkno...	no	no	telephone	may	mon
7	59	admin.	married	professional.course	no	no	no	telephone	may	mon
8	41	blue-collar	married	unknown	unkno...	no	no	telephone	may	mon
9	24	technician	single	professional.course	no	yes	no	telephone	may	mon
10	25	services	single	high.school	no	yes	no	telephone	may	mon
11	41	blue-collar	married	unknown	unkno...	no	no	telephone	may	mon
12	25	services	single	high.school	no	yes	no	telephone	may	mon
13	29	blue-collar	single	high.school	no	no	yes	telephone	may	mon
14	57	housemaid	divorced	basic.4y	no	yes	no	telephone	may	mon
15	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon
16	54	retired	married	basic.9y	unkno...	yes	yes	telephone	may	mon

Rows: 100

Data Dictionary

Column	Variable	Class
age	age of customer	
job	type of job	categorical: "admin.","blue-collar","entrepreneur","housemaid","management","retired","self-employed","services","student","technician","unemployed","unknown"
marital	marital status	categorical: "divorced","married","single","unknown"; note: "divorced" means divorced or widowed
education	highest degree of customer	categorical: "basic.4y","basic.6y","basic.9y","high.school","illiterate","professional.course","university.degree","unknown"
default	has credit in default?	categorical: "no","yes","unknown"
housing	has housing loan?	categorical: "no","yes","unknown"
loan	has personal loan?	categorical: "no","yes","unknown"
contact	contact communication type	categorical: "cellular","telephone"
month	last contact month of year	categorical: "jan", "feb", "mar", ..., "nov", "dec"
day_of_week	last contact day of the week	categorical: "mon","tue","wed","thu","fri"
campaign	number of contacts performed during this campaign and for this client	numeric, includes last contact
pdays	number of days that passed by after the client was last contacted from a previous campaign	numeric; 999 means client was not previously contacted
previous	number of contacts performed before this campaign and for this client	numeric
poutcome	outcome of the previous marketing campaign	categorical: "failure","nonexistent","success"
emp.var.rate	employment variation rate - quarterly indicator	numeric
cons.price.idx	consumer price index - monthly indicator	numeric
cons.conf.idx	consumer confidence index - monthly indicator	numeric
euribor3m	euribor 3 month rate - daily indicator	numeric
nr.employed	number of employees - quarterly indicator	numeric
y	has the client subscribed a term deposit?	binary: "yes","no"

Source of dataset.

Citations:

- 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
- S. Moro, R. Laureano and P. Cortez. Using Data Mining for Bank Direct Marketing: An Application of the CRISP-DM Methodology. In P. Novais et al. (Eds.), Proceedings of the European Simulation and Modelling Conference - ESM'2011, pp. 117-121, Guimaraes, Portugal, October, 2011. EUROSIS.

Don't know where to start?

Challenges are brief tasks designed to help you practice specific skills:

- 🗺️ **Explore**: What are the jobs of the people most likely to subscribe to a term deposit?
- 📊 **Visualize**: Create a plot to visualize the number of people subscribing to a term deposit by `month`.
- 🔎 **Analyze**: What impact does the number of contacts performed during the last campaign have on the likelihood that a customer subscribes to a term deposit?

Scenarios are broader questions to help you develop an end-to-end project for your portfolio:

You work for a financial services firm. The past few campaigns have not gone as well as the firm would have hoped, and they are looking for ways to optimize their marketing efforts.

They have supplied you with data from a previous campaign and some additional metrics such as the consumer price index and consumer confidence index. They want to know whether you can predict the likelihood of subscribing to a term deposit. The manager would also like to know what factors are most likely to increase a customer's probability of subscribing.

You will need to prepare a report that is accessible to a broad audience. It should outline your motivation, steps, findings, and conclusions.

```
# cleaning data set
# check duplicate value by columns
bank_job <- bank %>% distinct(job)
bank_marital <- bank %>% distinct(marital)
bank_edu <- bank %>% distinct(education)
bank_defu <- bank %>% distinct(default)
bank_housing <- bank %>% distinct(housing)
bank_loan <- bank %>% distinct(loan)
bank_contact <- bank %>% distinct(contact)
bank_month <- bank %>% distinct(month)
bank_day <-bank %>% distinct(day_of_week)
bank_poutcome <-bank%>% distinct(poutcome)
bank_y <-bank %>% distinct(y)

#convert unknown value to null for easy to handle
bank <- bank %>%
  mutate(across(c(job, marital, education, default, housing, loan), as.character)) %>%  # Ensure they are character
  mutate(across(c(job, marital, education, default, housing, loan), ~ na_if(., "unknown")))

colSums(is.na(bank)) # check null value by column name
bank_cleaned <- bank %>% na.omit() # remove null value in rows
```

```
age:       0 job:       330 marital:       80 education:       1731 default:       8597 housing:       990 loan:       990 contact:       0 month:       0
day_of_week:       0 duration:       0 campaign:       0 pdays:       0 previous:       0 poutcome:       0 emp.var.rate:       0 cons.price.idx:       0
cons.conf.idx:       0 euribor3m:       0 nr.employed:       0 y:       0
```

```
str(bank_cleaned)
```

```
tibble [30,488 × 21] (S3: tbl_df/tbl/data.frame)
 $ age           : num [1:30488] 56 37 40 56 59 24 25 25 29 57 ...
 $ job           : chr [1:30488] "housemaid" "services" "admin." "services" ...
 $ marital       : chr [1:30488] "married" "married" "married" "married" ...
 $ education     : chr [1:30488] "basic.4y" "high.school" "basic.6y" "high.school" ...
 $ default       : chr [1:30488] "no" "no" "no" "no" ...
 $ housing       : chr [1:30488] "no" "yes" "no" "no" ...
 $ loan          : chr [1:30488] "no" "no" "no" "yes" ...
 $ contact       : chr [1:30488] "telephone" "telephone" "telephone" "telephone" ...
 $ month         : chr [1:30488] "may" "may" "may" "may" ...
 $ day_of_week   : chr [1:30488] "mon" "mon" "mon" "mon" ...
 $ duration      : num [1:30488] 261 226 151 307 139 380 50 222 137 293 ...
 $ campaign      : num [1:30488] 1 1 1 1 1 1 1 1 1 1 ...
 $ pdays         : num [1:30488] 999 999 999 999 999 999 999 999 999 999 ...
 $ previous      : num [1:30488] 0 0 0 0 0 0 0 0 0 0 ...
 $ poutcome      : chr [1:30488] "nonexistent" "nonexistent" "nonexistent" "nonexistent" ...
 $ emp.var.rate  : num [1:30488] 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 ...
 $ cons.price.idx: num [1:30488] 94 94 94 94 94 ...
 $ cons.conf.idx : num [1:30488] -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 ...
 $ euribor3m     : num [1:30488] 4.86 4.86 4.86 4.86 4.86 ...
 $ nr.employed   : num [1:30488] 5191 5191 5191 5191 5191 ...
 $ y             : chr [1:30488] "no" "no" "no" "no" ...
```

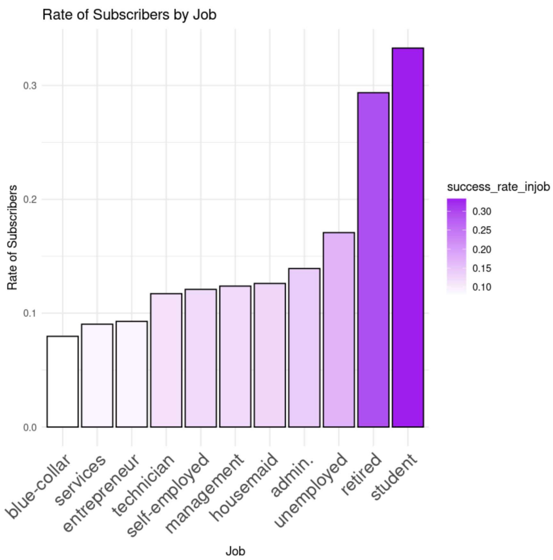
```
# What are the jobs of the people most likely to subscribe to a term deposit?


ratio_sub_injob <- bank %>%  # Filter and analyze subscription rate by job
  group_by(job) %>%
  summarise(
    total_customers = n(),
    total_y = sum(y == "yes"),
    success_rate_injob = total_y / total_customers
  ) %>%
  arrange(desc(success_rate_injob))  # Order by highest success rate

# Print results
print("The rate of subscribers in the campaign grouped by job")
print(ratio_sub_injob)

# Plot the bar chart
ggplot(ratio_sub_injob, aes(x = fct_reorder(job, success_rate_injob), y = success_rate_injob,fill = success_rate_injob))+
    geom_bar(stat = "identity", color = "black") +
    theme_minimal() +
    labs(title = "Rate of Subscribers by Job",
         x = "Job",
         y = "Rate of Subscribers") +
    theme(axis.text.x = element_text(size = 16,angle = 45, hjust = 1))+
    scale_fill_gradient(low = "white", high = "purple")  # Gradient from white to purple
```

```
[1] "The rate of subscribers in the campaign grouped by job"
# A tibble: 11 × 4
   job           total_customers total_y success_rate_injob
   <chr>                   <int>   <int>              <dbl>
 1 student                   610     203             0.333
 2 retired                  1216     357             0.294
 3 unemployed                738     126             0.171
 4 admin.                   8737    1216             0.139
 5 housemaid                 690      87             0.126
 6 management               2311     286             0.124
 7 self-employed            1092     132             0.121
 8 technician               5473     641             0.117
 9 entrepreneur             1089     101             0.0927
10 services                 2857     258             0.0903
11 blue-collar              5675     452             0.0796
```



Summary: Subscription Rate by Job

1. **Students (33.3%)** have the highest subscription rate, likely due to fewer financial commitments and an interest in secure savings.
2. **Retired individuals (29.4%)** follow, as they may have more disposable income and seek financial security.
3. **Unemployed (17.1%)** show moderate interest, possibly looking for financial stability.
4. **Administrative**, housemaids, and management roles (12%-14%) exhibit a reasonable subscription rate, likely due to stable incomes.
5. **Blue-collar workers (7.96%)** have the lowest rate, suggesting a preference for immediate financial needs over savings.
6. **Entrepreneurs** and service workers (~9%) may prioritize reinvesting in their businesses over term deposits. 🔹 **Targeting students**, retirees, and unemployed individuals with tailored financial plans could enhance subscription rates.

```r
# Create a plot to visualize the number of people subscribing to a term deposit by month.

str(bank$month) # check type of month

# convert charactors to factors
bank$month <- factor(bank$month,
                     levels = c("jan", "feb", "mar", "apr", "may", "jun",
                                "jul", "aug", "sep", "oct", "nov", "dec"),
                     labels = c("Jan", "Feb", "Mar", "Apr", "May", "Jun",
                                "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"),
                     ordered = TRUE)  # Ensures the factor has an inherent order

# find average customers apply in campaign by month
n_sub_by_month <- bank %>%
    group_by(month) %>%
    summarise(total_customers=n(),
             count_y=sum(y=="yes"),
             sucess_rate_inmonth=(count_y/total_customers)) %>%
    arrange(month)
print(n_sub_by_month)

# plot time serie graph x=month ,y=succes rate in month
library(ggplot2) # load ggplot labrary
ggplot(n_sub_by_month,aes(x=month,y=sucess_rate_inmonth,group=1))+
    geom_line(colour="blue")+ # line graph
    geom_point(color = "red")+  # Add points
    labs(title = "A number of subscriber to a deposit by month.",
         x = "Month",
         y = "Number of Subscribers")+
        theme_minimal()+
        theme(
        plot.title = element_text(size = 20, face = "bold"), # increas title size
        axis.title.x = element_text(size = 16), # increas x_title size
        axis.title.y = element_text(size = 16), # increas y_title size
        axis.text.x = element_text(size = 14),  # increase x-axis text
        axis.text.y = element_text(size = 14)) # increase y-axis text
```

```
 chr [1:30488] "may" "may" "may" "may" "may" "may" "may" "may" "may" "may" ...
# A tibble: 10 × 4
   month total_customers count_y sucess_rate_inmonth
   <ord>           <int>   <int>               <dbl>
 1 Mar               482     246              0.510
 2 Apr              2115     468              0.221
 3 May              9733     700              0.0719
 4 Jun              3614     452              0.125
 5 Jul              5081     512              0.101
 6 Aug              4673     533              0.114
 7 Sep               495     222              0.448
 8 Oct               642     287              0.447
 9 Nov              3496     365              0.104
10 Dec               157      74              0.471
```

Summary Key Observations:**

1. **Peak Contact Periods (May - August)** The highest number of customer contacts happened in May (13,769), followed by July (7,174), June (5,318), and August (6,178).

- Despite the high outreach, the success rate in May was the lowest (6.43%), suggesting a lower conversion rate despite high efforts.

2. **High Success Rate Months** (March, September, October, December)

- March (50.5%), September (44.9%), October (43.9%), and December (48.9%) showed the highest success rates.
- These months had fewer contacts but achieved a higher proportion of conversions, indicating better targeting or a more receptive audience.

3. **Low Success Rate in High Contact Months**, May had the most contacts (13,769) but one of the lowest success rates (6.43%).

- July and November also had high contacts but low success rates (9.05% and 10.1%, respectively).
- This suggests that high-volume outreach does not necessarily translate into higher conversion rates.

```
suppressPackageStartupMessages(library(tidyverse))
bank = read_delim('data/bank-marketing.csv', delim=";", show_col_types = FALSE)
```

```
# What impact does the number of contacts performed during the last campaign have on the likelihood that a customer subscribes
to a term deposit?

bank_cleaned


str(bank_cleaned$y)

bank_cleaned$y <- factor(bank_cleaned$y, levels = c("no", "yes"))
table(bank_cleaned$y, useNA = "always")

summary(bank_cleaned$y)

str(bank_cleaned$y)
bank_sum <- bank_cleaned %>%
    group_by(y) %>%
    summarise(avg_campaign = mean(campaign),
              median_campaign = median(campaign),
              max_campaign = max(campaign),
              min_campaign = min(campaign))
print(bank_sum)


# Wilcoxon test
wilcox.test(campaign ~ y, data = bank_cleaned)

# Logistic regression
model <- glm(y ~ campaign, data = bank_cleaned, family = binomial)
summary(model)

# How many time is the best time to contact
contact_analysis <- bank %>%
  group_by(campaign) %>%
  summarise(count_y=sum(y=="yes"),
            total_customers = n(),
            sucess_rate=(count_y/total_customers)) %>%
            arrange(campaign)

print(contact_analysis)
```

...	...	job	...	education	...	...	...	c.	...	da...
1	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon
5	59	admin.	married	professional.course	no	no	no	telephone	may	mon
6	24	technician	single	professional.course	no	yes	no	telephone	may	mon
7	25	services	single	high.school	no	yes	no	telephone	may	mon
8	25	services	single	high.school	no	yes	no	telephone	may	mon
9	29	blue-collar	single	high.school	no	no	yes	telephone	may	mon
10	57	housemaid	divorced	basic.4y	no	yes	no	telephone	may	mon
11	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon
12	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon
13	50	blue-collar	married	basic.9y	no	yes	yes	telephone	may	mon
14	30	unemployed	married	high.school	no	no	no	telephone	may	mon
15	55	retired	single	high.school	no	yes	no	telephone	may	mon
16	41	technician	single	high.school	no	yes	no	telephone	may	mon

Rows: 4,761 ⚠ truncated from 30,488 rows

```
 Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
   no   yes  <NA>
26629  3859     0
```

```
no:      26629 yes:      3859
```

```
 Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
# A tibble: 2 × 5
  y     avg_campaign median_campaign max_campaign min_campaign
  <fct>        <dbl>           <dbl>        <dbl>        <dbl>
```

```
1 no            2.59              2           43            1
2 yes           2.03              2           23            1
```

```
    Wilcoxon rank sum test with continuity correction

data:  campaign by y
W = 56874760, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

```

Call:
glm(formula = y ~ campaign, family = binomial, data = bank_cleaned)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.64525    0.02746  -59.91   <2e-16 ***
campaign    -0.12683    0.01036  -12.25   <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: 23160  on 30487  degrees of freedom
Residual deviance: 22958  on 30486  degrees of freedom
AIC: 22962

Number of Fisher Scoring iterations: 5
```

```
# A tibble: 42 × 4
   campaign count_y total_customers sucess_rate
      <dbl>   <int>           <int>       <dbl>
 1        1    2300           17642      0.130
 2        2    1211           10570      0.115
 3        3     574            5341      0.107
 4        4     249            2651      0.0939
 5        5     120            1599      0.0750
 6        6      75             979      0.0766
 7        7      38             629      0.0604
 8        8      17             400      0.0425
 9        9      17             283      0.0601
10       10      12             225      0.0533
# ℹ 32 more rows
```

From the result Summary of Results:

1. Interpretation: The variable campaign significantly influences the outcome, and for every one-unit increase in the campaign variable, the log-odds of a positive outcome decrease by 0.12683.

2. Practical Impact : Depending on the scale of campaign, this suggests that increased campaign activity may be associated with a lower likelihood of the target event occurring..

Business insights

1. The results show that as the number of contact attempts increases, customers are more likely to reject the campaign. This is likely because they become annoyed when they receive too many calls.
2. The optimal number of contact attempts is one. Therefore, employees should maximize their efforts during the first call and use a well-structured script to engage customers effectively.
3. The company should explore alternative ways to reach customers instead of relying solely on phone calls. Options include SMS, online advertisements, and other digital marketing strategies.

```r
# find which variable have significatant with likly to subscribed in campaign

str(bank_cleaned)

# convert all charactors to factors
bank_cleaned[] <- lapply(bank_cleaned, function(x) if(is.character(x)) factor(x) else x)

# Fit the logistic regression model
# Assuming 'y' is the response variable and all other columns are predictors
model <- glm(y ~ ., family = binomial, data = bank_cleaned)

# Summary of the model to see which variables are significant
summary(model)
```

```
tibble [30,488 × 21] (S3: tbl_df/tbl/data.frame)
 $ age           : num [1:30488] 56 37 40 56 59 24 25 25 29 57 ...
 $ job           : Factor w/ 11 levels "admin.","blue-collar",..: 4 8 1 8 1 10 8 8 2 4 ...
 $ marital       : Factor w/ 3 levels "divorced","married",..: 2 2 2 2 2 3 3 3 3 1 ...
 $ education     : Factor w/ 7 levels "basic.4y","basic.6y",..: 1 4 2 4 6 6 4 4 4 1 ...
 $ default       : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ housing       : Factor w/ 2 levels "no","yes": 1 2 1 1 1 2 2 2 1 2 ...
 $ loan          : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 2 1 ...
 $ contact       : Factor w/ 2 levels "cellular","telephone": 2 2 2 2 2 2 2 2 2 2 ...
 $ month         : Factor w/ 10 levels "apr","aug","dec",..: 7 7 7 7 7 7 7 7 7 7 ...
 $ day_of_week   : Factor w/ 5 levels "fri","mon","thu",..: 2 2 2 2 2 2 2 2 2 2 ...
 $ duration      : num [1:30488] 261 226 151 307 139 380 50 222 137 293 ...
 $ campaign      : num [1:30488] 1 1 1 1 1 1 1 1 1 1 ...
 $ pdays         : num [1:30488] 999 999 999 999 999 999 999 999 999 999 ...
 $ previous      : num [1:30488] 0 0 0 0 0 0 0 0 0 0 ...
 $ poutcome      : Factor w/ 3 levels "failure","nonexistent",..: 2 2 2 2 2 2 2 2 2 2 ...
 $ emp.var.rate  : num [1:30488] 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 ...
 $ cons.price.idx: num [1:30488] 94 94 94 94 94 ...
 $ cons.conf.idx : num [1:30488] -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 -36.4 ...
 $ euribor3m     : num [1:30488] 4.86 4.86 4.86 4.86 4.86 ...
 $ nr.employed   : num [1:30488] 5191 5191 5191 5191 5191 ...
 $ y             : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
 - attr(*, "na.action")= 'omit' Named int [1:10700] 2 4 8 11 14 18 20 22 27 28

Call:
glm(formula = y ~ ., family = binomial, data = bank_cleaned)

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -2.740e+02  4.187e+01  -6.544 5.98e-11 ***
age                         -2.202e-03  2.727e-03  -0.807 0.419423
jobblue-collar              -2.119e-01  9.079e-02  -2.334 0.019573 *
jobentrepreneur             -1.705e-01  1.396e-01  -1.222 0.221821
jobhousemaid                 4.055e-02  1.661e-01   0.244 0.807101
jobmanagement               -2.075e-02  9.177e-02  -0.226 0.821089
jobretired                   3.364e-01  1.205e-01   2.791 0.005250 **
jobself-employed            -7.976e-02  1.253e-01  -0.637 0.524301
jobservices                 -1.610e-01  9.542e-02  -1.687 0.091559 .
jobstudent                   2.614e-01  1.244e-01   2.102 0.035565 *
jobtechnician                3.660e-02  7.618e-02   0.481 0.630867
jobunemployed                3.295e-02  1.383e-01   0.238 0.811663
maritalmarried              -3.084e-03  7.510e-02  -0.041 0.967246
maritalsingle                2.759e-02  8.502e-02   0.324 0.745566
educationbasic.6y            1.139e-01  1.439e-01   0.792 0.428629
educationbasic.9y            2.448e-02  1.108e-01   0.221 0.825087
educationhigh.school         8.818e-02  1.054e-01   0.837 0.402724
educationilliterate          1.595e+00  8.637e-01   1.847 0.064771 .
educationprofessional.course 1.349e-01  1.143e-01   1.180 0.237841
educationuniversity.degree   2.336e-01  1.055e-01   2.213 0.026870 *
defaultyes                  -7.289e+00  1.135e+02  -0.064 0.948790
housingyes                  -2.117e-02  4.501e-02  -0.470 0.638095
loanyes                     -5.676e-02  6.228e-02  -0.911 0.362119
contacttelephone            -6.670e-01  8.295e-02  -8.042 8.87e-16 ***
monthaug                     8.510e-01  1.301e-01   6.542 6.06e-11 ***
monthdec                     2.312e-01  2.271e-01   1.018 0.308752
monthjul                     4.723e-02  1.064e-01   0.444 0.657161
monthjun                    -6.701e-01  1.346e-01  -4.977 6.46e-07 ***
monthmar                     2.089e+00  1.550e-01  13.477  < 2e-16 ***
monthmay                    -4.357e-01  8.925e-02  -4.882 1.05e-06 ***
monthnov                    -4.631e-01  1.336e-01  -3.467 0.000526 ***
```

```
monthoct                    2.508e-01  1.683e-01   1.490 0.136217    
monthsep                    4.660e-01  1.961e-01   2.376 0.017488 *  
day_of_weekmon             -6.788e-02  7.318e-02  -0.928 0.353648    
day_of_weekthu              1.238e-01  7.110e-02   1.741 0.081693 .  
day_of_weektue              1.587e-01  7.307e-02   2.172 0.029872 *  
day_of_weekwed              2.434e-01  7.261e-02   3.353 0.000801 ***
duration                    4.558e-03  8.407e-05  54.221  < 2e-16 ***
campaign                   -4.026e-02  1.297e-02  -3.104 0.001908 ** 
pdays                      -9.746e-04  2.352e-04  -4.143 3.43e-05 ***
previous                   -5.285e-02  6.364e-02  -0.830 0.406280    
poutcomenonexistent         4.673e-01  1.019e-01   4.584 4.57e-06 ***
poutcomesuccess             9.284e-01  2.294e-01   4.048 5.17e-05 ***
emp.var.rate               -1.899e+00  1.509e-01 -12.580  < 2e-16 ***
cons.price.idx              2.443e+00  2.739e-01   8.921  < 2e-16 ***
cons.conf.idx               2.127e-02  8.427e-03   2.523 0.011622 *  
euribor3m                   2.883e-01  1.463e-01   1.971 0.048711 *  
nr.employed                 8.128e-03  3.447e-03   2.358 0.018361 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 23160  on 30487  degrees of freedom
Residual deviance: 13902  on 30440  degrees of freedom
AIC: 13998

Number of Fisher Scoring iterations: 10
```

Summary Significant Variables (p-value < 0.05):

Conclusion: Variables with significant p-values (p-value < 0.05) have a statistically significant relationship with the likelihood of subscribing to the campaign.

Key predictors include contact method, month of the year, duration of the call, previous campaign outcome, and certain job and education categories.

Duration and poutcome (previous campaign outcome) seem to have the strongest relationship with the outcome.

Key Points:

p-value < 0.05: The variable likely has a real, non-random relationship with the outcome.

p-value ≥ 0.05: The evidence is insufficient to conclude that the variable affects the outcome, and the relationship could be due to chance.