TERM DEPOSIT SUBSCRIPTIONS: A PREDICTIVE ANALYSIS OF CUSTOMER BEHAVIOR

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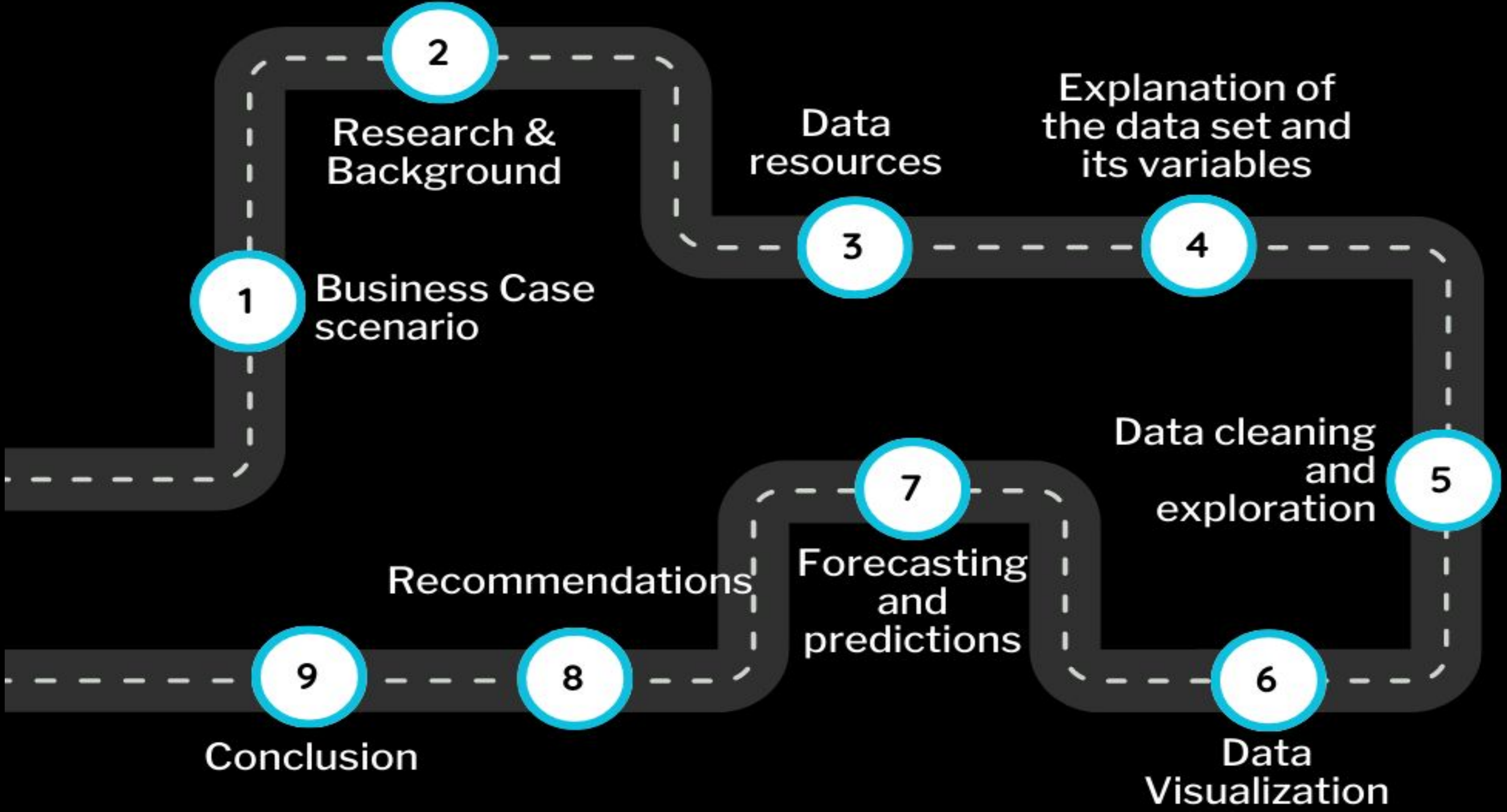
OVERVIEW OF THE PRESENTATION



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BUSINESS CASE SCENARIO

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BUSINESS CASE SCENARIO

- Our client is The Continental Ltd, one of the most prominent banks in Portugal.

- The bank has consulted us regarding a telephonic marketing campaign as they want to attract their customers to subscribe to term deposits.

THE CONTINENTAL LTD.

FIRST STEP TOWARDS THE FUTURE

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RESEARCH AND BACKGROUND

- The bank wants an analytical report so that based on the analytical findings and predictions they can build a target customer profile for their term deposits.

- The bank has provided data of it’s previous marketing campaign.

- Telemarketing is a strategy that helps a firm to get in touch with its customers directly and understand if they are willing to purchase their products (Borugadda, Nandru, & Madhavaiah, 2021).

- Many financial companies have adopted telemarketing to communicate with their existing customers, understand their needs and provide better services (Borugadda et al, 2021).

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WHAT IS A TERM DEPOSIT?

A term deposit is a form of deposit account that a customer has with a bank in which money is locked for a certain period.

Term deposits are short-term investments with maturity period ranging from one month to many years.

Term deposits gives higher interest rates than regular savings accounts.

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BUSINESS CASE OBJECTIVES

Build a target customer profile for term deposits.

Analyze customer demographics to forecast customer savings patterns.

Analyze if existing loans affect customer's savings decision.

Understand if the duration of a campaign call can influence customer's decision to subscribe to term deposits.

Help the bank build an efficient marketing campaign.

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INTRODUCTION TO DATA SET

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INTRODUCTION TO DATA SET

```
'data.frame':   45211 obs. of  17 variables:
 $ age      : int  58 44 33 47 33 35 28 42 58 43 ...
 $ job      : chr  "management" "technician" "entrepreneur" "blue-collar" ...
 $ marital  : chr  "married" "single" "married" "married" ...
 $ education: chr  "tertiary" "secondary" "secondary" "unknown" ...
 $ default  : chr  "no" "no" "no" "no" ...
 $ balance  : int  2143 29 2 1506 1 231 447 2 121 593 ...
 $ housing  : chr  "yes" "yes" "yes" "yes" ...
 $ loan     : chr  "no" "no" "yes" "no" ...
 $ contact  : chr  "unknown" "unknown" "unknown" "unknown" ...
 $ day      : int  5 5 5 5 5 5 5 5 5 5 ...
 $ month    : chr  "may" "may" "may" "may" ...
 $ duration : int  261 151 76 92 198 139 217 380 50 55 ...
 $ campaign : int  1 1 1 1 1 1 1 1 1 1 ...
 $ pdays    : int  -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 ...
 $ previous : int  0 0 0 0 0 0 0 0 0 0 ...
 $ poutcome : chr  "unknown" "unknown" "unknown" "unknown" ...
 $ y        : chr  "no" "no" "no" "no" ...
```

- The data set is taken from Kaggle which is an open source platform that has enormous amount of data.

- The link to the data set is:

https://www.kaggle.com/datasets/prakharrathi25/banking-dataset-marketing-targets

- The data set has 45211 rows and 17 variables.

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SAMPLE OF THE DATA SET

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
2	33	admin.	married	tertiary	no	882	no	no	telephone	21	oct	39	1	151	3	failure	no
3	33	services	married	secondary	no	3444	yes	no	telephone	21	oct	144	1	91	4	failure	yes
4	36	managem	married	tertiary	no	0	yes	no	telephone	23	oct	140	1	143	3	failure	yes
5	51	admin.	single	secondary	no	3132	no	no	telephone	5	nov	449	1	176	1	failure	no
6	33	unemploy	divorced	secondary	no	1005	yes	no	telephone	10	nov	175	1	174	2	failure	no
7	34	admin.	married	tertiary	no	899	yes	no	unknown	12	nov	114	1	170	3	failure	yes
8	30	managem	single	tertiary	no	1243	yes	no	telephone	13	nov	86	1	174	1	failure	no
9	44	entrepren	married	tertiary	no	1631	yes	no	cellular	17	nov	81	1	195	2	failure	no
10	51	managem	divorced	tertiary	no	119	no	no	cellular	17	nov	200	1	165	2	failure	no
11	51	technician	married	secondary	no	58	yes	no	cellular	17	nov	79	1	129	2	failure	no
12	44	managem	married	tertiary	no	6203	yes	yes	cellular	17	nov	58	1	188	1	failure	no
13	34	technician	single	secondary	no	105	yes	no	cellular	17	nov	303	1	196	2	failure	no
14	49	managem	married	tertiary	no	1533	no	no	cellular	17	nov	324	1	172	1	failure	no
15	47	housemai	married	tertiary	no	228	yes	no	cellular	17	nov	80	1	118	1	failure	no
16	40	managem	single	secondary	no	1623	yes	no	cellular	17	nov	161	1	167	2	failure	no
17	47	blue-collar	married	secondary	no	1484	no	no	cellular	17	nov	297	1	119	3	failure	no
18	54	technician	single	secondary	no	198	yes	yes	cellular	17	nov	120	1	171	2	failure	no
19	45	technician	married	secondary	no	1477	yes	no	cellular	17	nov	75	1	132	1	failure	no
20	39	admin.	married	secondary	no	401	yes	no	cellular	17	nov	396	1	129	2	failure	no
21	39	blue-collar	married	primary	no	3324	no	no	cellular	17	nov	96	1	131	1	failure	no
22	37	managem	married	tertiary	yes	0	no	no	cellular	17	nov	44	1	123	2	failure	no
23	58	admin.	married	unknown	no	0	yes	no	cellular	17	nov	219	1	186	2	failure	no
24	43	technician	married	secondary	no	1865	yes	no	cellular	17	nov	155	1	186	1	failure	no
25	50	managem	married	secondary	no	633	no	yes	telephone	17	nov	302	1	111	6	failure	no
26	56	retired	married	secondary	no	2749	yes	yes	cellular	17	nov	38	1	172	2	failure	no
27	51	entrepren	married	tertiary	no	209	no	no	cellular	17	nov	130	1	111	2	failure	no

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KEY VARIABLES

Variable	Variable Type	Description
Age	Integer	Age of the customer
Job	Character	Type of Job the customer does
Marital	Character	Marital status of the customer
Balance	Integer	Average yearly balance
Housing	Character	The customer has housing loan or not
Loan	Character	The customer has personal loan or not
Month	Character	Last contact month
Duration	Integer	Last contact duration is seconds
poutcome	Character	Outcome of the previous campaign
Campaign	Integer	Number of times the customer was contacted during the campaign

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DATA CLEANING AND TRANSFORMATION

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R PACKAGES USED IN THE BUSINESS CASE

1. Caret- Used to train models
2. Rpart- Used for building and visualizing decision trees.
3. Dplyr- Used for data manipulation.
4. Ggplot2- Used for data visualizations.
5. Lubridate- Helps working with date and time.
6. Forecast- Provides tools for time series forecasting.

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DATA CLEANING

- This dataset has no missing values but it contains “unknown” values
- Dropped outliers in the column “balance”.
- Replaced “unknown” values in the column “poutcome” with mode.

```
Q1 <- quantile(banking_termdep$balance, 0.25)
Q3 <- quantile(banking_termdep$balance, 0.75)
IQR <- Q3 - Q1

lower <- Q1 - 1.5 * IQR
upper <- Q3 + 1.5 * IQR


banking_termdep <- banking_termdep[banking_termdep$balance >= lower & banking_termdep$balance <= upper,]

banking_termdep$contact <- NULL
banking_termdep$ID <- NULL
```

```
set.seed(123)
banking_termdep$poutcome[banking_termdep$poutcome == "unknown"] <- mode_poutcome
```

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DATA TRANSFORMATION

- Dropped rows with “duration” less than 5 seconds.
- Changed “unknown” in the column “education” and “job” as “others”.
- Converted all variables to factors.
- We are left with 38,824 observations after data cleaning and transformation.

```r
banking_termdep$job <- as.factor(banking_termdep$job)
banking_termdep$marital <- as.factor(banking_termdep$marital)
banking_termdep$education <- as.factor(banking_termdep$education)
banking_termdep$default <- as.factor(banking_termdep$default)
banking_termdep$housing <- as.factor(banking_termdep$housing)
banking_termdep$loan <- as.factor(banking_termdep$loan)
banking_termdep$month <- as.factor(banking_termdep$month)
banking_termdep$day <- as.factor(banking_termdep$day)
banking_termdep$contact <- NULL
banking_termdep$ID <- NULL
```

```r
banking_termdep <- banking_termdep[!banking_termdep$duration < 5,]

banking_termdep$job <- ifelse(banking_termdep$job == "unknown", "other", banking_termdep$job)
banking_termdep$education <- ifelse(banking_termdep$education == "unknown", "other", banking_termdep$education)
```

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DATA EXPLORATION

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1. UNDERSTAND CUSTOMER DEMOGRAPHICS

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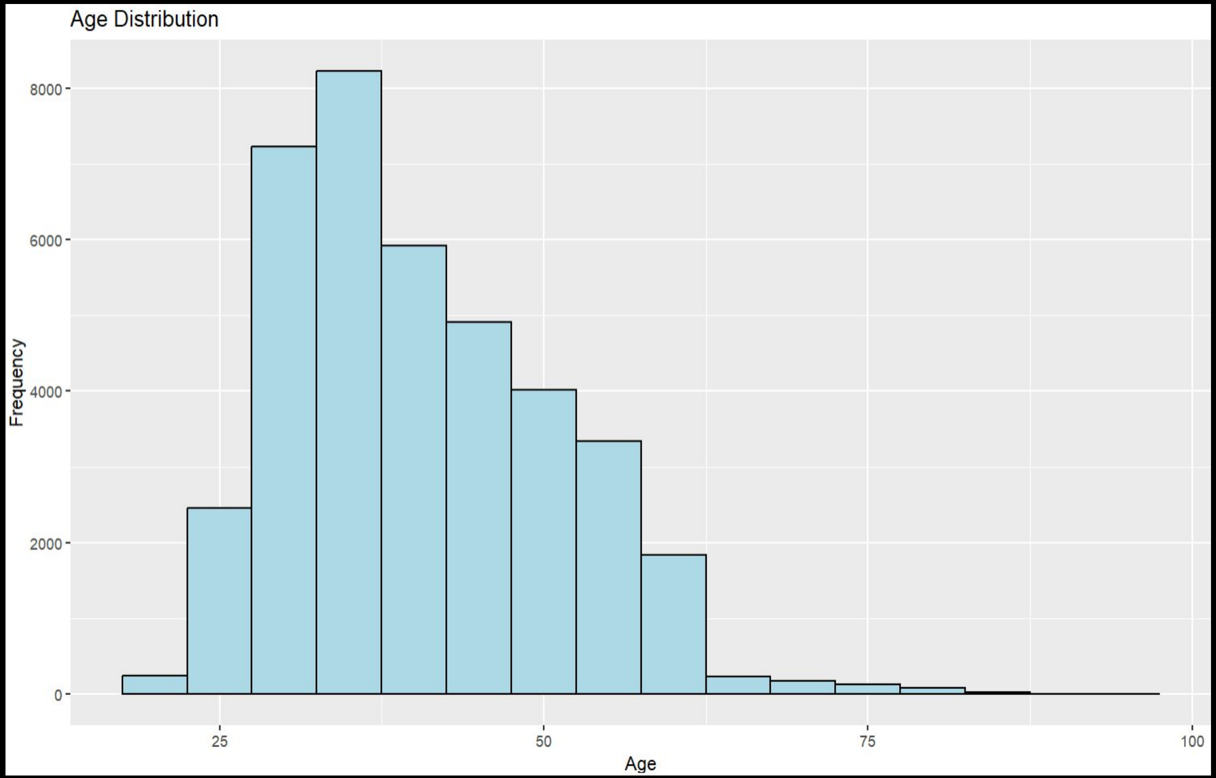
DISTRIBUTION OF AGE




```
ggplot(data = banking_termdep, aes(x = age)) +
  geom_histogram(binwidth = 5, color = "black", fill = "lightblue") +
  ggtitle("Age Distribution") +
  xlab("Age") + ylab("Frequency")
```

- In this marketing campaign, the customers are between the age group 18-95.
- Majority of the customers called are in the age group 30-40.

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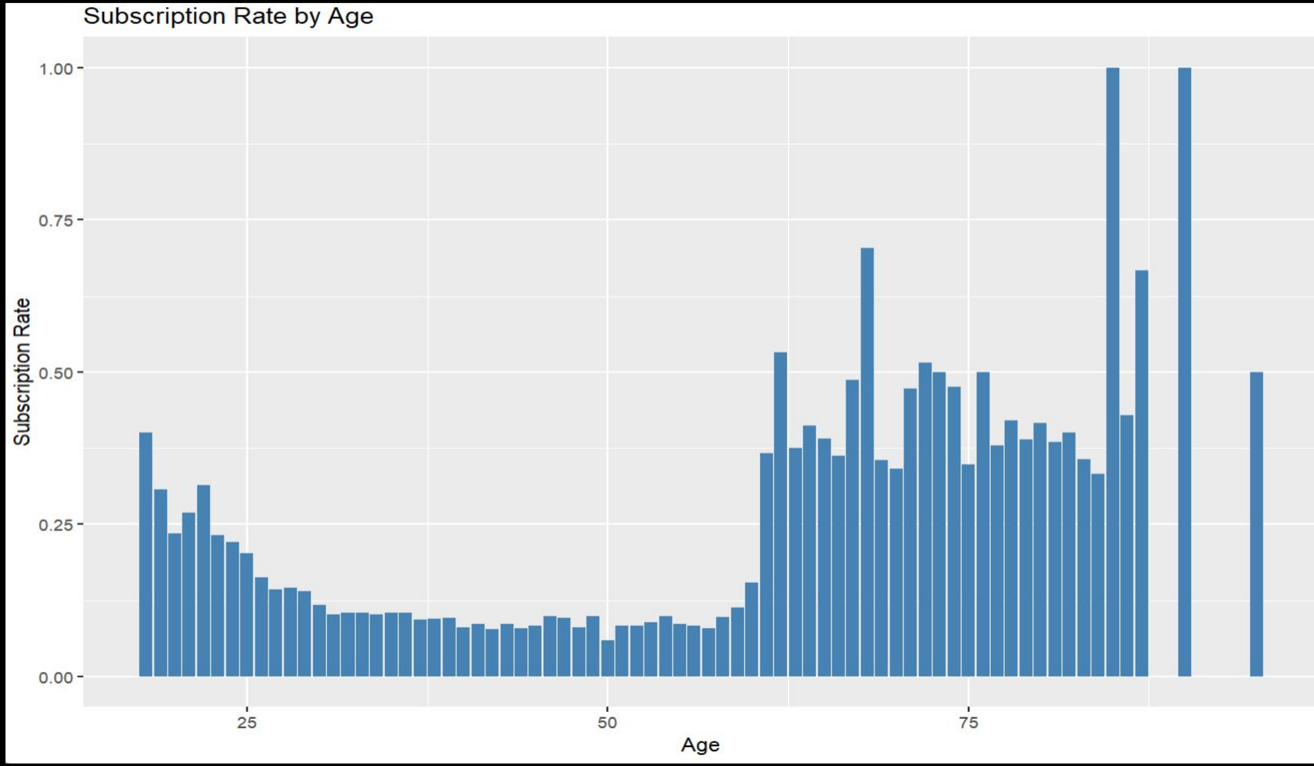
VISUALIZING SUBSCRIPTION RATE BY AGE




```r
sub_rate_by_age <- banking_termdep %>%
  group_by(age) %>%
  summarize(sub_rate = mean(y == "yes"))

ggplot(sub_rate_by_age, aes(x = age, y = sub_rate)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  xlab("Age") +
  ylab("Subscription Rate") +
  ggtitle("Subscription Rate by Age")
```

- Customers aged 60 or older have the most subscription rate.
- Customers aged between 18 to 30 have higher subscription rate than customers over 30.
- The youngest and oldest customers provide more than half of all subscriptions.

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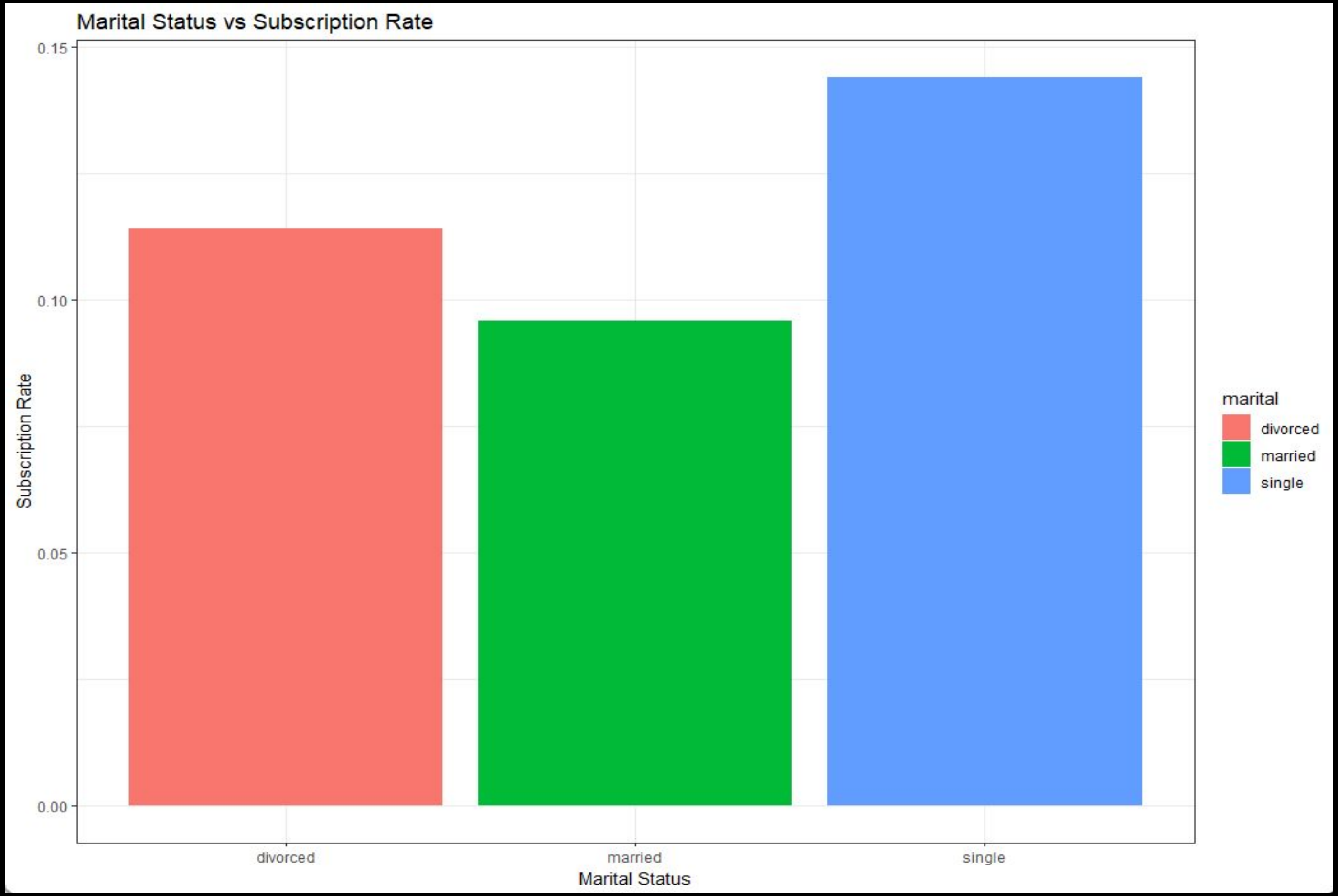
SUBSCRIPTION RATE VS MARITAL STATUS



From the bar plot, we can see that the maximum people who subscribed to term deposit are single.

```r
sub_marital <- banking_termdep %>%
  group_by(marital) %>%
  summarize(subscription_rate = mean(subscription))


ggplot(sub_marital, aes(x = marital, y = subscription_rate, fill = marital)) +
  geom_bar(stat = "identity") +
  ggtitle("Marital Status vs Subscription Rate") +
  xlab("Marital Status") +
  ylab("Subscription Rate") +
  theme_bw()
```

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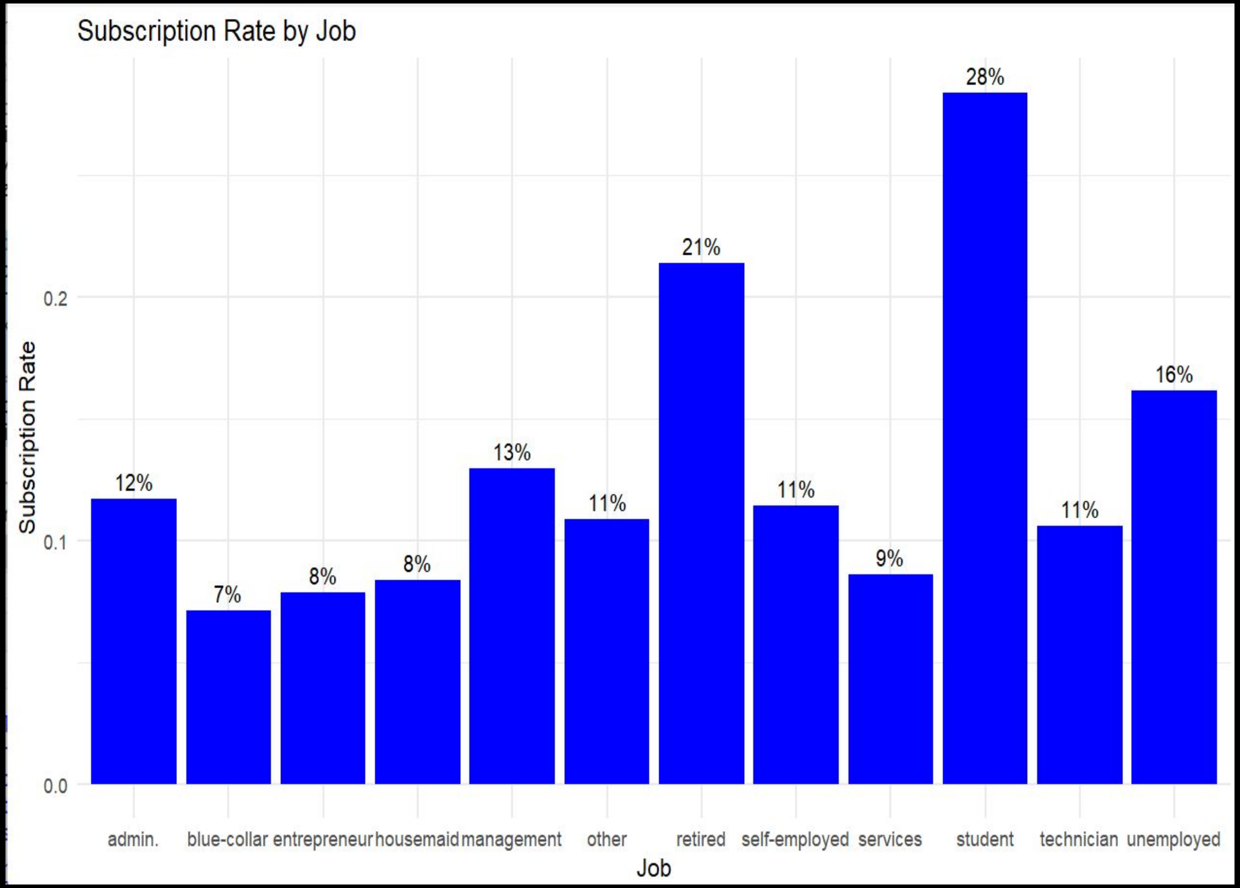
VISUALIZING THE RATE OF SUBSCRIPTION BY JOB CATEGORY




```
sub_job <- banking_termdep %>%
  group_by(job) %>%
  summarize(subscription_rate = mean(subscription))


ggplot(sub_job, aes(x = job, y = subscription_rate)) +
  geom_bar(stat = "identity", fill = "blue") +
  geom_text(aes(label = paste0(round(subscription_rate*100), "%")),
            vjust = -0.5, size = 3.5) +`
labs(x = "Job", y = "Subscription Rate",
     title = "Subscription Rate by Job") +
  theme_minimal()
```

- More than half of subscribers are students or retired people.

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2. EVALUATE IMPORTANT CAMPAIGN VARIABLES

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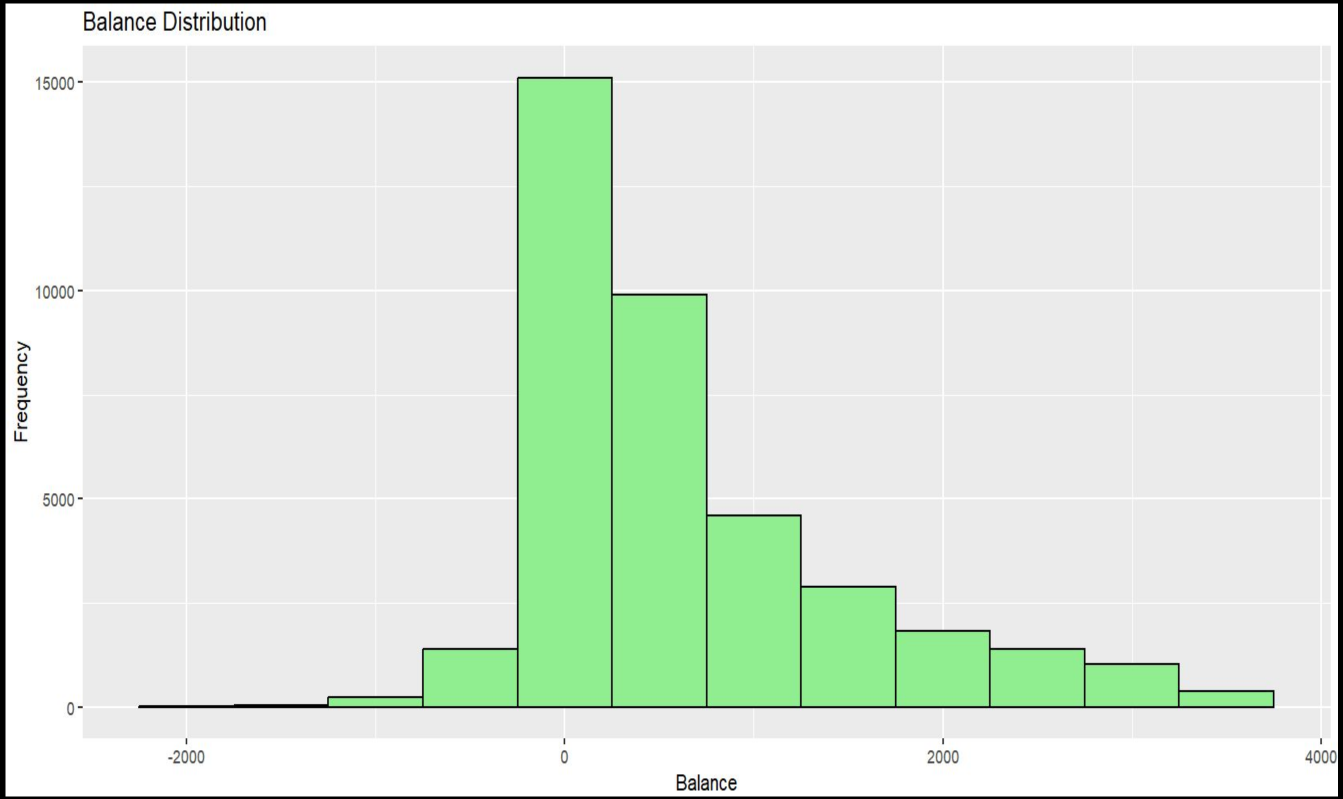
DISTRIBUTION OF BALANCE




```r
ggplot(data = banking_termdep, aes(x = balance)) +
  geom_histogram(binwidth = 500, color = "black", fill = "lightgreen") +
  ggtitle("Balance Distribution") +
  xlab("Balance") + ylab("Frequency")
```

- After dropping the outliers, the range of balance is from -6847 to a maximum of 10443 euros.
- The distribution of balance has a huge standard deviation.

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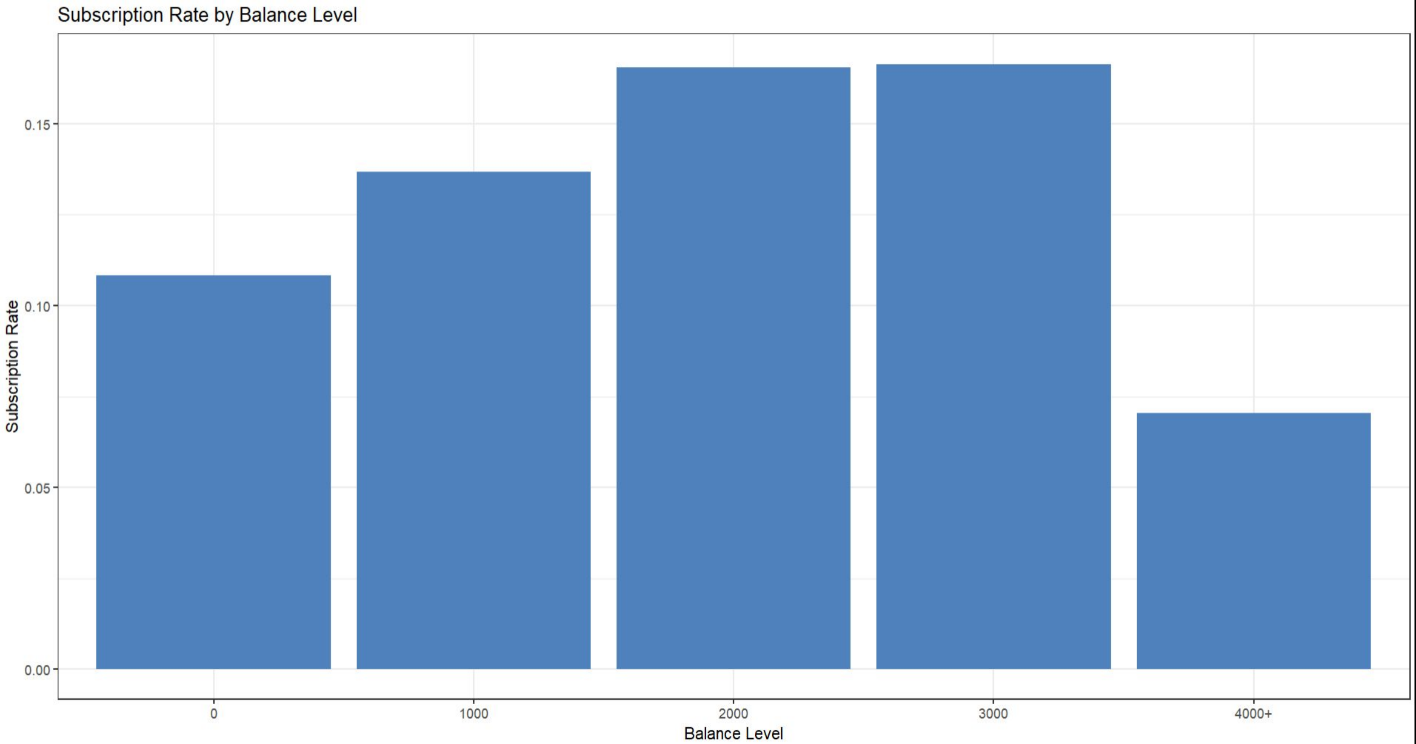
VISUALIZING SUBSCRIPTION RATE BY BALANCE




```
sub_bal <- banking_termdep %>%
  mutate(balance_level = cut(balance, c(0, 1000, 2000, 3000, Inf)),
         subscribed = ifelse(banking_termdep$y == "yes", 1, 0)) %>%
  group_by(balance_level) %>%
  summarise(subscription_rate = mean(subscribed)) %>%
  ungroup()


ggplot(sub_bal, aes(x = balance_level, y = subscription_rate)) +
  geom_bar(stat = "identity", fill = "#4F81BD") +
  labs(x = "Balance Level", y = "Subscription Rate") +
  scale_x_discrete(labels = c("0", "1000", "2000", "3000", "4000+")) +
  ggtitle("Subscription Rate by Balance Level") +
  theme_bw()
```

- Customers with negative or very low balance have returned a low subscription rate.
- Customers with balance between 1000-3000 euros have returned a significantly high subscription rate.

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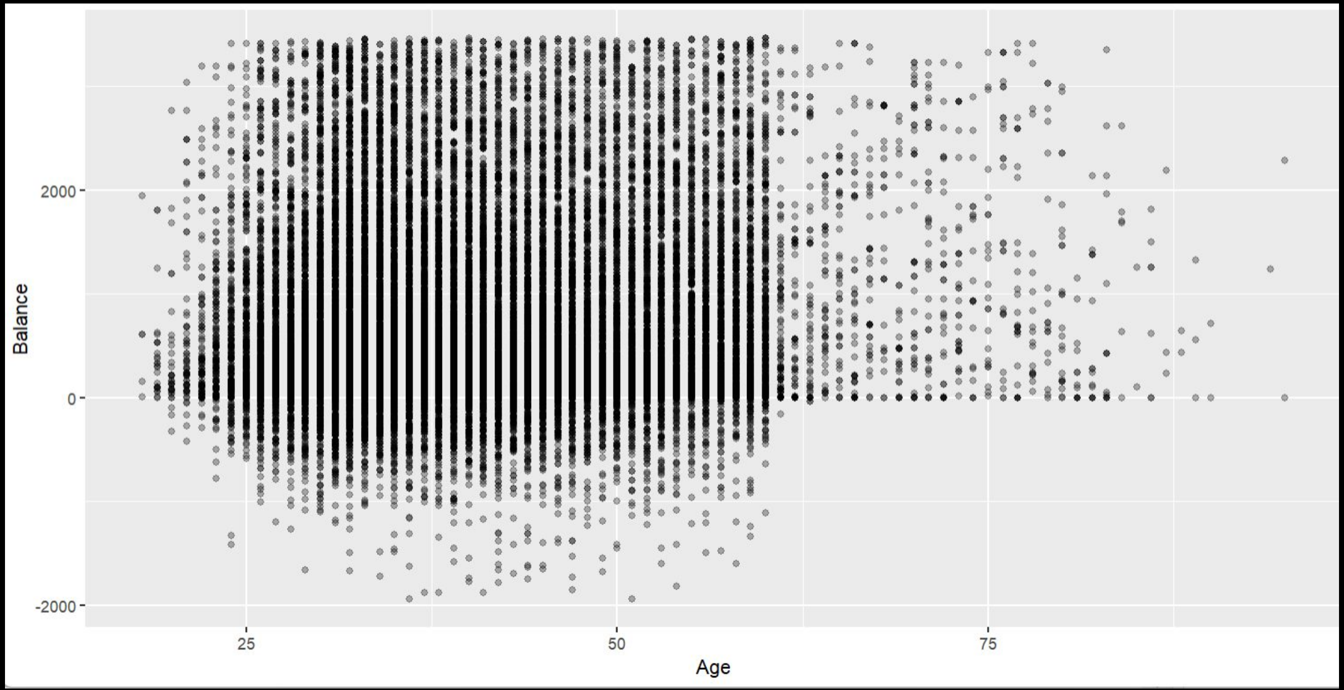
RELATIONSHIP BETWEEN AGE & BALANCE



- Customers above the age of 60 have considerably lower balances.

- We could believe that most individuals retire at the age of 60 and no longer have a steady source of income.

```
ggplot(banking_termdep, aes(x = age, y = balance)) +
  geom_point(alpha = 0.3, size = 1.5) +
  labs(title = "Relationship between Age and Balance",
       x = "Age", y = "Balance")
```

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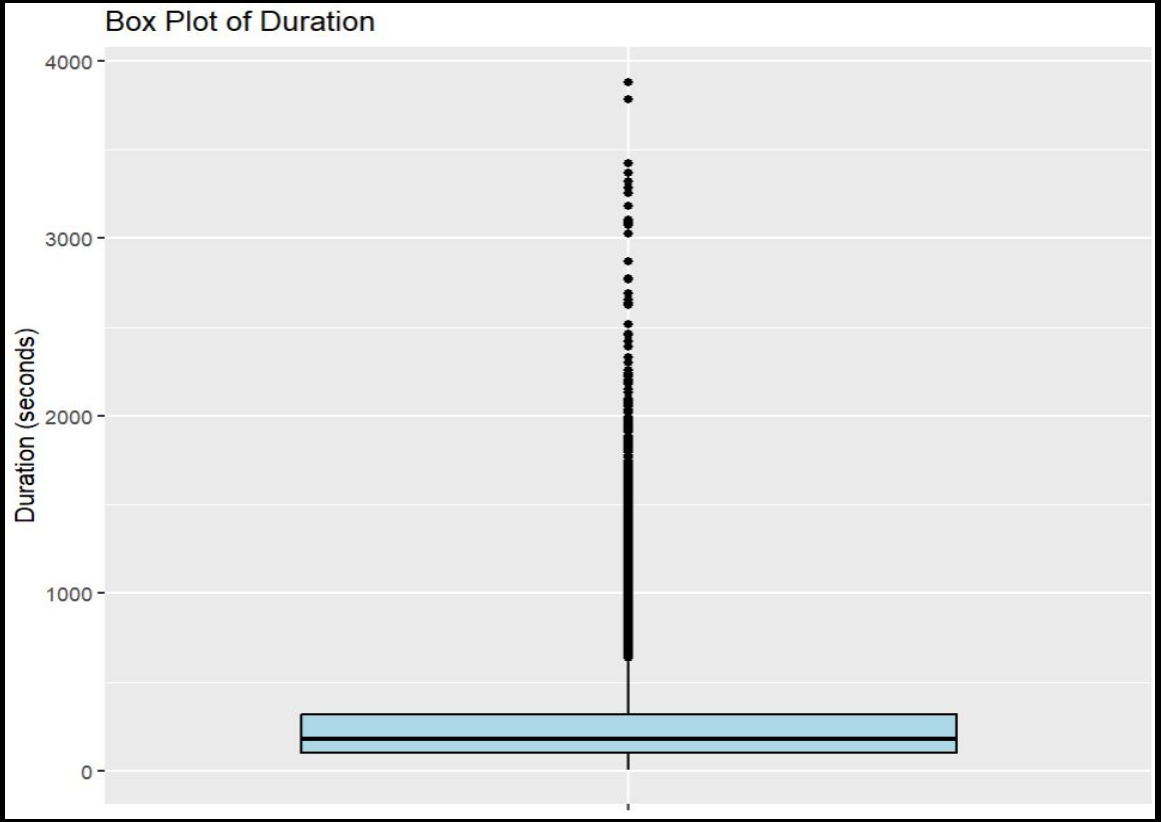
DISTRIBUTION OF CALL DURATION




```r
ggplot(banking_termdep, aes(x = "", y = duration)) +
  geom_boxplot(fill = "lightblue", color = "black") +
  xlab("") + ylab("Duration (seconds)") +
  ggtitle("Box Plot of Duration")
```

- From the box plot, it can be observed that the call duration for each customer is very low.
- The median of the call duration is 179 seconds and the interquartile range is 213 seconds.

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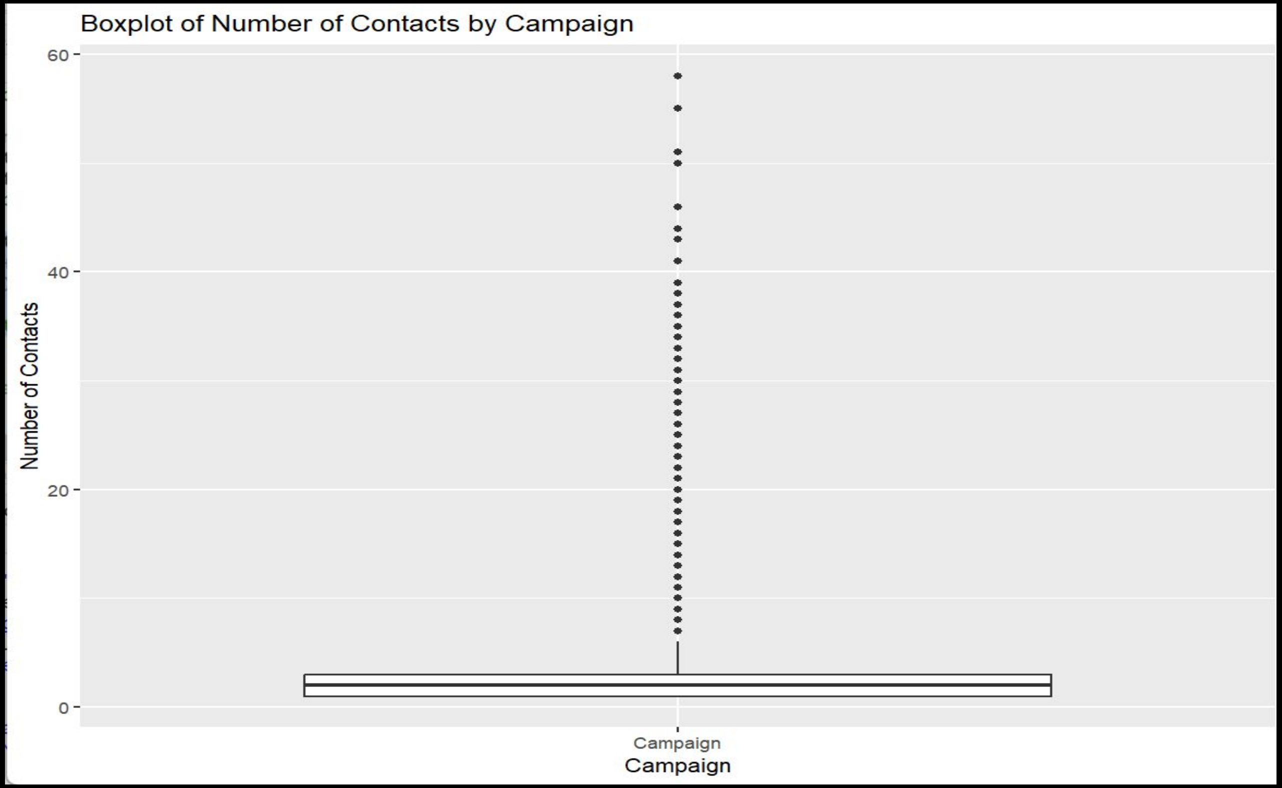
DISTRIBUTION OF THE NUMBER OF TIMES THE CUSTOMER WAS CONTACTED




```
ggplot(banking_termdep, aes(x = "Campaign", y = campaign)) +
  geom_boxplot() +
  xlab("Campaign") +
  ylab("Number of Contacts") +
  ggtitle("Boxplot of Number of Contacts by Campaign")
```

- From the box plot, we can see that most of the customers were contacted more than once.
- However, certain customers were called up to 58 times.

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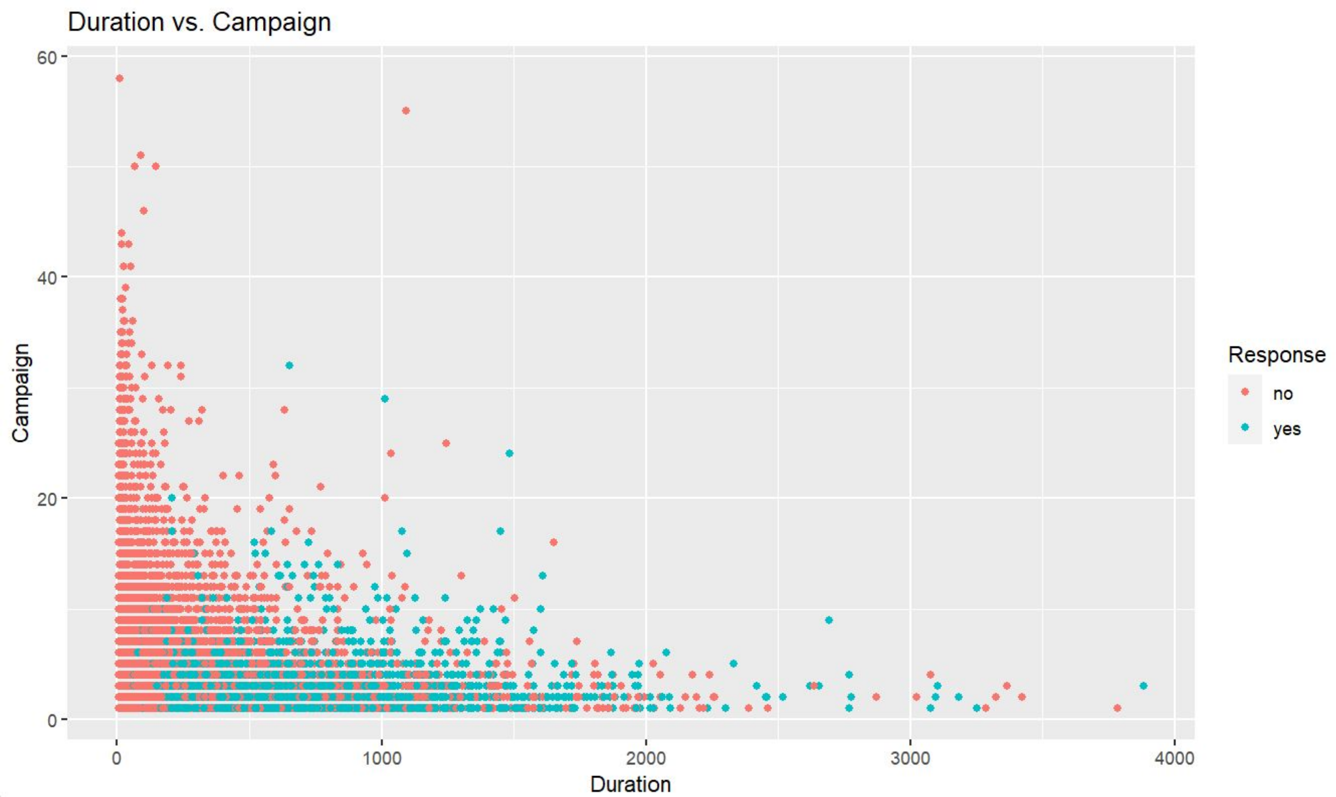
RELATIONSHIP BETWEEN DURATION & CAMPAIGN CALLS: WITH SUBSCRIPTION OUTCOME




```r
ggplot(banking_termdep, aes(x=duration, y=campaign, color=y)) +
  geom_point() +
  labs(title="Duration vs. Campaign", x="Duration", y="Campaign", color="Response")
```

- Customers who have subscribed have been called less number of times and have higher call duration.
- Customers are most likely to reject the term deposits if they have been contacted for more than 5 times.
- We might believe that the bank should stop calling the customers if they have been contacted 5 times.

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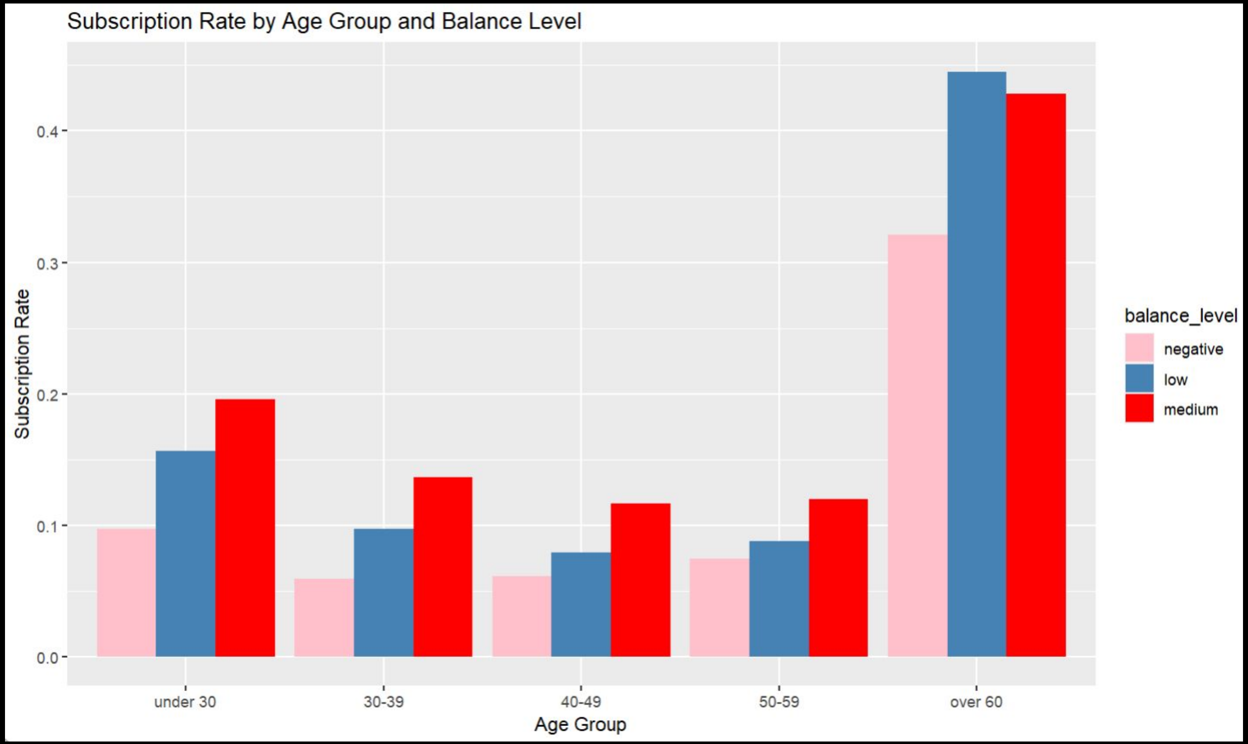
VISUALIZING THE RATE OF SUBSCRIPTION BY GROUPING AGE AND BALANCE




```r
age_balance <- banking_termdep %>%
  group_by(age_group, balance_level) %>%
  summarize(sub_rate = mean(y == "yes"))

ggplot(age_balance, aes(x = age_group, y = sub_rate, fill = balance_level)) +
  geom_bar(stat = "identity", position = "dodge") +
  scale_fill_manual(values = c("pink", "steelblue", "red", "blue")) +
  xlab("Age Group") +
  ylab("Subscription Rate") +
  ggtitle("Subscription Rate by Age Group and Balance Level")
```

- We plotted this graph to see whether there is a pattern across all ages with respect to balance that suggests the most probable subscription behavior.

- In every age group, the percentage of subscription grows with balance.

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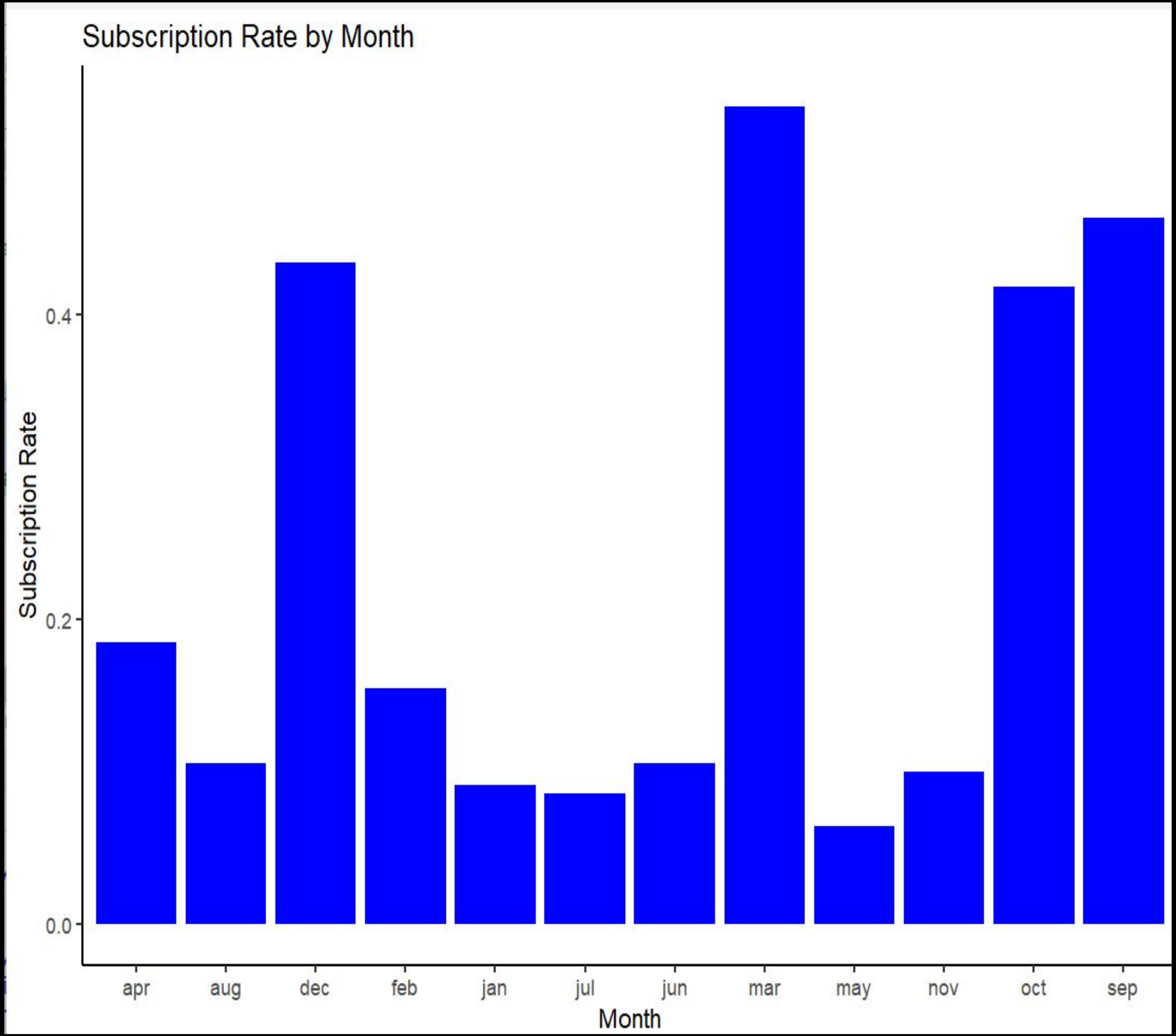
VISUALIZING THE RATE OF SUBSCRIPTION BY CAMPAIGN MONTH




```r
month_summary <- banking_termdep %>%
  group_by(month) %>%
  summarize(sub_rate = mean(y == "yes", na.rm = TRUE))

ggplot(month_summary, aes(x = month, y = sub_rate)) +
  geom_col(fill = "blue") +
  labs(title = "Subscription Rate by Month", x = "Month", y = "Subscription Rate") +
  theme_classic()
```

•The month with the highest rate of subscription was March, followed by September, October, and December.

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BUSINESS INSIGHTS FROM DATA EXPLORATION

- While young people may lack necessary funds for high risk investments and therefore opt for term deposits, the goal of elderly individuals is to save for retirement.
- The marital status of most people who subscribed to term deposit is single followed by divorced.
- The age group for target customers is below 30 and above 60.
- Customers that are receptive have a balance of 1000-3000 euros.
- The job profile of target customers is students and retired people.
- The months with highest subscription rates were March, September, October, and December.

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PREDICTIVE ANALYTICS

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1. CLASSIFICATION ALGORITHM – DECISION TREE

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SPLITTING THE DATASET INTO TRAIN AND TEST DATA FOR CLASSIFICATION

- set.seed(123) divides the data set into a training and testing set depending on the subscription variable.
- The training set contains 70% of the data, while the testing set contains the remaining 30% of the data set.
- We chose k = 10, which means that the data will be divided into 10 parts, and the model will be trained and run three times on each of these divided parts.

```
set.seed(123)
trainIndex <- createDataPartition(banking_termdep$y, p=0.7, list=FALSE)
training_data <- banking_termdep[trainIndex,]
testing_data <- banking_termdep[-trainIndex,]
```

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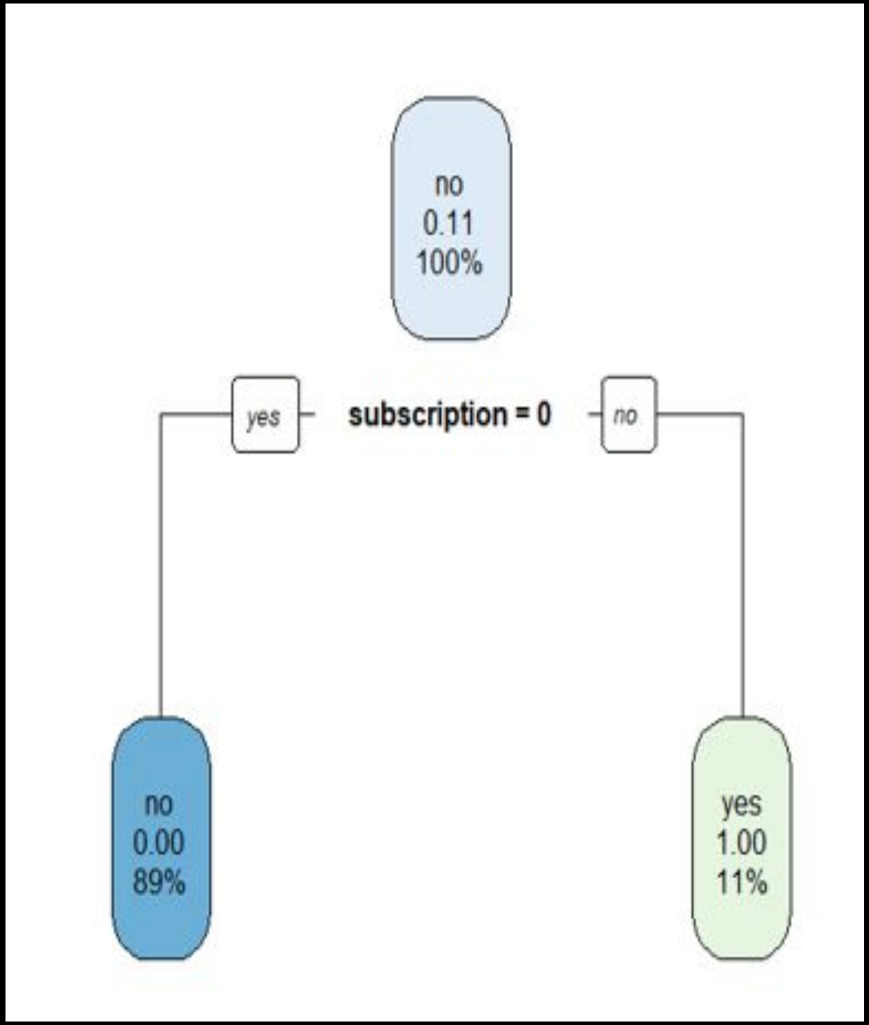
DECISION TREE



According to the decision tree plot, based on customer demographics and prior campaigns, the classification model forecasts that 11% of total customers would subscribe to the term deposit, while 89% will not.

```
data_model <- rpart(y ~ ., data=training_data, method="class")
data_pred <- predict(data_model, testing_data, type="class")

data_predf = factor(data_pred)
testing_data$y = factor(testing_data$y)

dt_cm <- confusionMatrix(data_predf, testing_data$y)
print(dt_cm)

rpart.plot(data_model)
```

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FINDINGS FROM CONFUSION MATRIX

```
Confusion Matrix and Statistics

          Reference
Prediction    no   yes
       no  10353     0
       yes     0  1294

               Accuracy : 1
                 95% CI : (0.9997, 1)
    No Information Rate : 0.8889
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 1

 Mcnemar's Test P-Value : NA

            Sensitivity : 1.0000
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 1.0000
             Prevalence : 0.8889
         Detection Rate : 0.8889
   Detection Prevalence : 0.8889
      Balanced Accuracy : 1.0000

       'Positive' Class : no
```

- The model predicted all 10353 'no' cases and 1294 'yes' cases correctly.
- The confusion matrix shows 95% accuracy.
- Both the sensitivity and specificity are 1. This indicates that the model has accurately predicted all positive and negative instances.
- The prevalence is 0.8889 which means that 88.89% of the instances in the test set are the response “no”.
- We might conclude that the model is quite accurate.

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2. LOGISTIC REGRESSION

DEPENDENCY OF SUBSCRIPTION ON IMPORTANT CAMPAIGN FACTORS

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	31622.129[a]	.022	.043

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted y 0	Predicted y 1	Percentage Correct
Step 1	y	0	39049	873	97.8
		1	3984	1305	24.7
	Overall Percentage				89.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	month	.002	.006	.176	1	.675	1.002
	housing(1)	.887	.031	824.989	1	<.001	2.428
	loan(1)	.665	.050	176.745	1	<.001	1.944
	campaign	-.141	.008	279.328	1	<.001	.868
	Constant	-2.743	.064	1857.277	1	.000	.064

a. Variable(s) entered on step 1: month, housing, loan, campaign.

- Logistic regression was used to determine the dependence of subscription rate on housing and personal loans, call duration, and campaign month.
- The model successfully classified 89.3% of subscribers and explained 43.0% of the variance in subscription rate.
- Housing loan, personal loan, and number of campaign calls all significantly contribute to the model ($p < 0.001$).
- The subscription rate does not depend on the month the of the campaign($p = 0.675$).

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BUSINESS INSIGHTS FROM PREDICTIVE ANALYTICS

- It is predicted that only 11% customers tend to subscribe to term deposits.
- 89% of customers do not subscribe to term deposits.
- The customer profile created from data exploration should be used for the next campaign to increase the subscription rate from 11%.
- The subscription rate depends on the existing loans the customer has and also the number of times the customer has been contacted in a campaign.
- The subscription rate does not depend on the month the campaign was run.

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FORECASTING ANALYSIS

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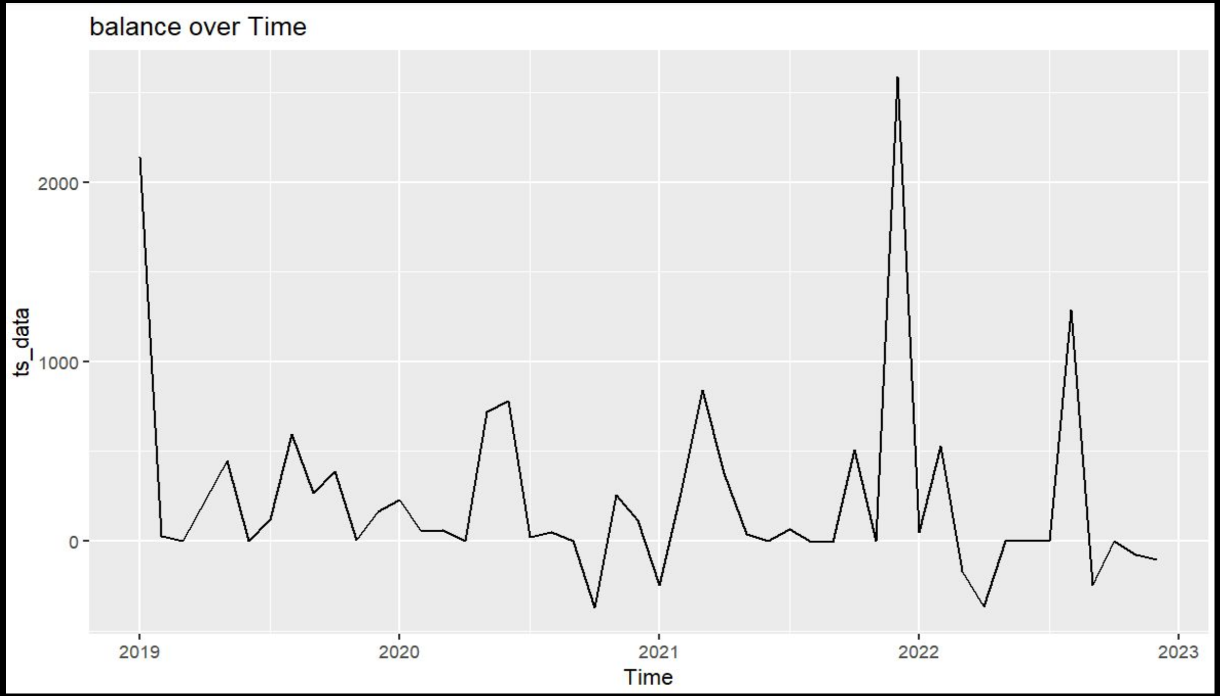
TIME SERIES ANALYSIS TO CHECK TRENDS IN CUSTOMER BALANCE




```
library(lubridate)
library(forecast)

banking_termdep$date <- as.Date(paste(banking_termdep$year, banking_termdep$month, banking_termdep$day, sep="-"), format="%Y-%m-%d")
banking_termdep$date <- as.Date(banking_termdep$date, format = "%Y-%m-%d")
ts_data <- ts(banking_termdep$balance, start = c(min(banking_termdep$year), 1), end = c(max(banking_termdep$year), 12), frequency = 12)

autoplot(ts_data) + labs(title = "balance over Time")
```

- The graph demonstrates that the "balance" variable has a positive trend over time.
- The graph shows seasonality, which indicates that the data has regular patterns or cycles that reoccur.
- These cycles appear to repeat themselves every year, with the lowest points in balance occurring towards the start of each year and the highest points coming near the middle of each year.

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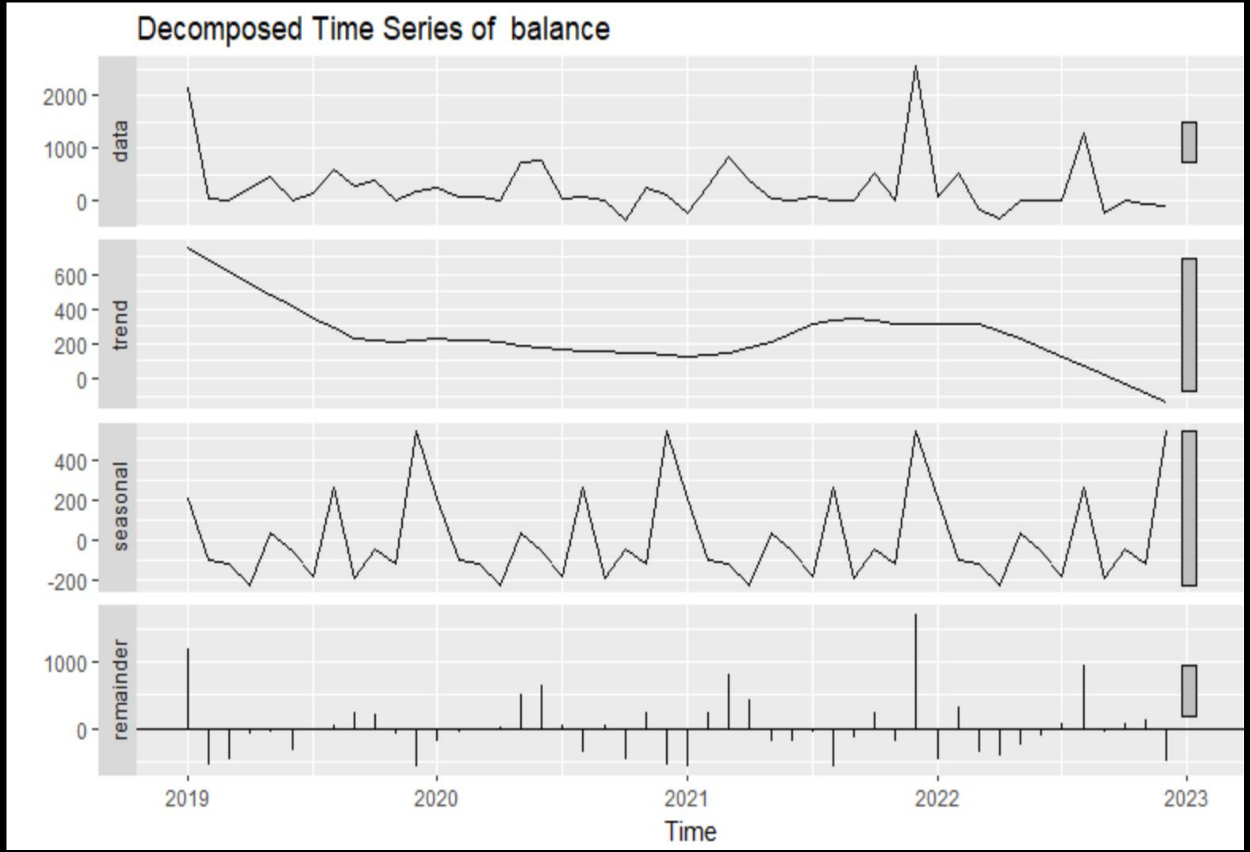
FINDINGS FROM STL DECOMPOSED TIME SERIES PLOT




```r
decomp_ts <- stl(ts_data, s.window = "periodic")

autoplot(decomp_ts) + labs(title = "Decomposed Time Series of  balance")
```

- The original time series data is shown in the top panel of the graph, where the y-axis indicates the variable "balance" and the x-axis indicates the time period.
- The trend looks to be pretty constant over time, with a little downward slope.
- The seasonal component looks consistent throughout, with slight changes.
- Throughout the time period, the remainder component appears to be volatile.

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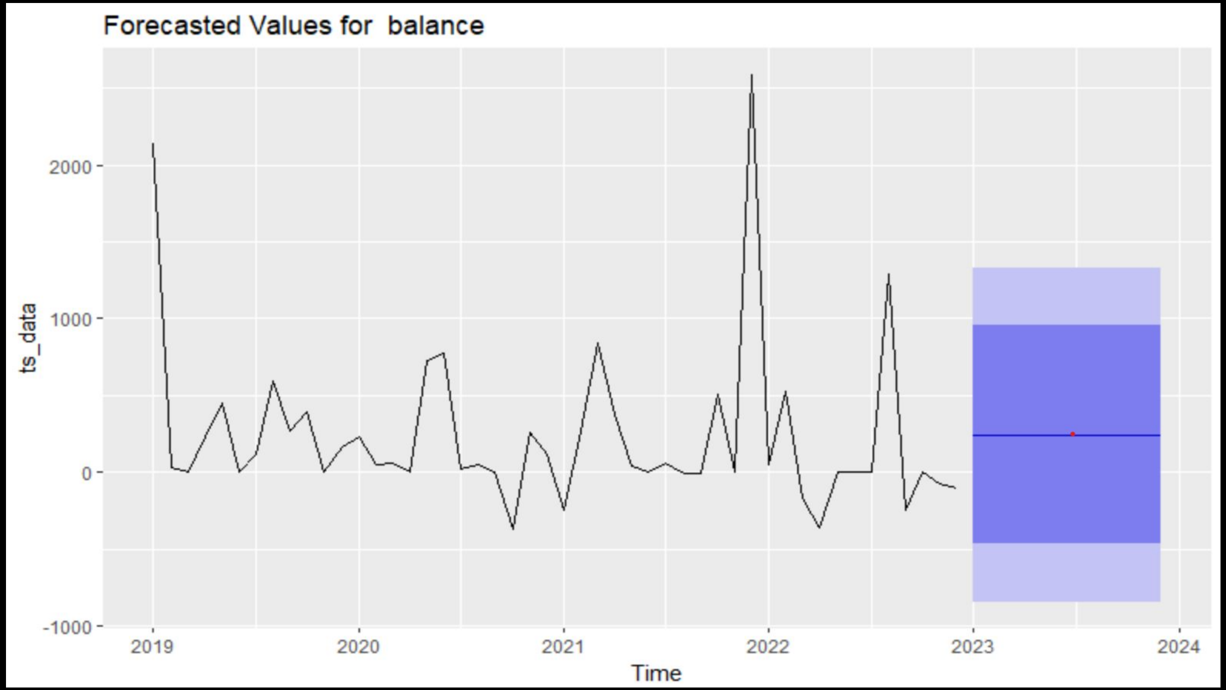
TIME SERIES FORECAST FOR BALANCE




```r
fit <- auto.arima(ts_data)

forecast_ts <- forecast(fit, h = 12)

autoplot(forecast_ts) + labs(title = "Forecasted Values for  balance")
```

- The time series forecasts the values for balance over the next 12 months.
- The forecasted and actual values appear to follow a similar pattern, indicating that the model captures the underlying trends in the data.
- The 80% prediction interval suggests that there is an 80% likelihood that the actual values will fall within this range.

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RECOMMENDATIONS AND PREDICTIONS

Data Exploration

- The age group for target customers is below 30 and above 60.
- Customers that are receptive have a balance of 1000-3000 euros.
- The job profile of target customers is students and retired people.
- The months with highest subscription rates were March, September, October, and December.
- We might believe that if the customer has previously made a long duration call, he or she is more likely to sign up for a term deposit.
- The bank should stop calling a customer for term deposit subscription if they have been called 5 times.

RECOMMENDATIONS AND PREDICTIONS

Predictive Analytics:

- 11% subscribers are likely to subscribe to term deposits. The bank should target the built customer profile to increase subscription rate.
- Bank should look at the existing loans that the customer has to understand the risk profile of the customer.

Forecasting:

- Term deposits should be recommended during the middle and end of the year when the customers maintain a positive balance.

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CONCLUSION

Exploratory data analysis was used to create a target consumer profile.

The classification model was created to predict how customers would respond to the term deposit.

The regression model was created to assess the subscription's dependency on other crucial elements such as prior loans and campaign calls.

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REFERENCES

Das, A., & Das, P. (2002). Rate of interest on term deposits–A micro level study. *online publication*.

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Thank You

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