Question_03

gowtham_1p23mb010

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3. Using the "bank-full" dataset, perform the following tasks with detailed analysis and appropriate visualizations:

i. Load the dataset and examine its structure using basic commands

```
df = read.csv("D:/Data Science for Marketing-I/data/bank-full.csv")
```

```
str(df)
```

```
## '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" ...
##  $ Target    : chr  "no" "no" "no" "no" ...
```

```
summary(df)
```

```
##       age            job              marital           education        
##  Min.   :18.00   Length:45211       Length:45211       Length:45211       
##  1st Qu.:33.00   Class :character   Class :character   Class :character   
##  Median :39.00   Mode  :character   Mode  :character   Mode  :character   
##  Mean   :40.94                                                           
##  3rd Qu.:48.00                                                           
##  Max.   :95.00                                                           
##    default            balance         housing              loan          
##  Length:45211       Min.   : -8019   Length:45211       Length:45211       
##  Class :character   1st Qu.:    72   Class :character   Class :character   
##  Mode  :character   Median :   448   Mode  :character   Mode  :character   
##                     Mean   :  1362                                         
##                     3rd Qu.:  1428                                         
##                     Max.   :102127                                         
##    contact               day             month              duration     
##  Length:45211       Min.   : 1.00   Length:45211       Min.   :   0.0  
##  Class :character   1st Qu.: 8.00   Class :character   1st Qu.: 103.0  
##  Mode  :character   Median :16.00   Mode  :character   Median : 180.0  
##                     Mean   :15.81                      Mean   : 258.2  
##                     3rd Qu.:21.00                      3rd Qu.: 319.0  
##                     Max.   :31.00                      Max.   :4918.0  
##     campaign          pdays          previous          poutcome        
##  Min.   : 1.000   Min.   : -1.0   Min.   :  0.0000   Length:45211       
##  1st Qu.: 1.000   1st Qu.: -1.0   1st Qu.:  0.0000   Class :character   
##  Median : 2.000   Median : -1.0   Median :  0.0000   Mode  :character   
##  Mean   : 2.764   Mean   : 40.2   Mean   :  0.5803                      
##  3rd Qu.: 3.000   3rd Qu.: -1.0   3rd Qu.:  0.0000                      
##  Max.   :63.000   Max.   :871.0   Max.   :275.0000                      
##     Target         
##  Length:45211       
##  Class :character   
##  Mode  :character   
##                     
##                     
##                     
```

```
head(df)
```

```
##   age           job  marital education default balance housing loan contact day
## 1  58    management  married  tertiary      no    2143     yes   no unknown   5
## 2  44    technician   single secondary      no      29     yes   no unknown   5
## 3  33 entrepreneur  married secondary      no       2     yes  yes unknown   5
## 4  47   blue-collar  married   unknown      no    1506     yes   no unknown   5
## 5  33       unknown   single   unknown      no       1      no   no unknown   5
## 6  35    management  married  tertiary      no     231     yes   no unknown   5
##   month duration campaign pdays previous poutcome Target
## 1   may      261        1    -1        0  unknown     no
## 2   may      151        1    -1        0  unknown     no
## 3   may       76        1    -1        0  unknown     no
## 4   may       92        1    -1        0  unknown     no
## 5   may      198        1    -1        0  unknown     no
## 6   may      139        1    -1        0  unknown     no
```

```
dim(df)
```

```
## [1] 45211    17
```

Interpretation: This step checks the data type, column names, and basic summary statistics to understand the dataset's structure.

ii. Create a new variable called "conversion" by transforming the categorical values in the "Target" column into numerical representations.

```
df$conversion=ifelse(df$Target=="yes",1,0)
df$conversion=ifelse(df$Target=="yes",1,0)
```

Interpretation:This converts the target variable into numerical format, making it easier for regression and machine learning models.

iii. Calculate and interpret the Conversion Rate. How does the code implement this calculation, and what does it reveal about the target variable distribution?

```
print(sum(df$conversion)/nrow(df)*100)
```

```
## [1] 11.69848
```

Interpretation:The conversion rate is the percentage of customers who accepted the offer. A higher rate suggests a successful campaign.

iv. Analyze and visualize Conversion Rates by Marital Status: Explain how conversion rates are computed for each marital status. Create a bar chart to display these rates and interpret the visualization.

```
library(dplyr)
```

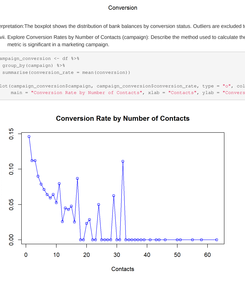
```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
marital_conversion <- df %>%
  group_by(marital) %>%
  summarise(conversion_rate = mean(conversion))

barplot(marital_conversion$conversion_rate, names.arg = marital_conversion$marital,
        col = "skyblue", main = "Conversion Rate by Marital Status", ylab = "Rate")
```

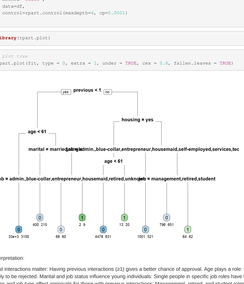


Interpretation:This visual shows how conversion rates vary by marital status, helping target specific customer groups.

v. Investigate Default Rates by Conversion Status using a pivot table and pie chart visualizations. What insights can you draw from these visual representations?

```
default_conversion <- table(df$default, df$conversion)

pie(table(df$default), labels = c("No Default", "Default"), main = "Default by Conversion Status")
```



Interpretation:This reveals how default status correlates with conversion, providing insights into customer financial reliability.

vi. Use a boxplot to analyze the relationship between conversion status and bank balance distributions. Why are outliers excluded, and what does the plot tell you about customer balance patterns?

```
boxplot(balance ~ conversion, data = df, col = c("lightblue", "pink"),
        main = "Bank Balance Distribution by Conversion", xlab = "Conversion", ylab = "Balance")
```

Interpretation:The boxplot shows the distribution of bank balances by conversion status. Outliers are excluded to focus on typical patterns.

vii. Explore Conversion Rates by Number of Contacts (campaign): Describe the method used to calculate these rates, and explain why this metric is significant in a marketing campaign.

```
campaign_conversion <- df %>%
  group_by(campaign) %>%
  summarise(conversion_rate = mean(conversion))

plot(campaign_conversion$campaign, campaign_conversion$conversion_rate, type = "o", col = "blue",
     main = "Conversion Rate by Number of Contacts", xlab = "Contacts", ylab = "Conversion Rate")
```


Interpretation:This tracks how conversion rates change with the number of contacts, optimizing campaign efforts.

viii. Describe how to encode categorical variables, such as job, marital, housing, and loan, for machine learning models.

```
# One-hot encoding for categorical variables
df_encoded <- model.matrix(~ job + marital + housing + loan - 1, data = df)
```

Interpretation:Categorical variables are encoded as binary indicators, enabling their use in machine learning algorithms.

ix. Build a Decision Tree Model using the provided features:Explain the selection of features and the target variable?

```
library(rpart)
```

```
#complexity parameter
fit <- rpart(
  conversion ~ age +  campaign + previous + housing + job + marital,
  method="class",
  data=df,
  control=rpart.control(maxdepth=4, cp=0.0001)
)
```

```
library(rpart.plot)
```

```
# plot tree
rpart.plot(fit, type = 0, extra = 1, under = TRUE, cex = 0.8, fallen.leaves = TRUE)
```


Interpretation:

Pasti interactions matter: Having previous interactions (≥1) gives a better chance of approval. Age plays a role: Older individuals (≥61) are more likely to be rejected. Marital and job status influence young individuals: Single people in specific job roles have better approval chances. Housing loans and job type affect approvals for those with previous interactions: Management, retired, and student roles have a higher chance of approval.

Visualize the decision tree using appropriate plotting techniques. How does this visualization help in understanding the decision-making process of the model?

```
rpart.plot(fit, cex = 0.8, fallen.leaves = TRUE)
```


Interpretation:

This decision tree functions similar to the previous one, but the key difference is that it provides the **majority percentage** at each decision point.

Since we **cannot use** `type = 0` and `extra = 1` together:

- `type = 0` displays only the basic structure of the tree.
- `extra = 1` enhances the tree by adding **outcome details** and **data distribution** within each node.

This means the visualization not only shows the decision logic but also highlights the **dominant class percentage** at each step.