1. Introduction

A term deposit is a amount collected by the financial institution on agreed rate of interest over a fixed tenure or conditions. To increase the capacity of bank to lend more money to the customers in the form of loans, bank always seeks to raise higher term deposit from the customer. There are many methods to sell term deposits to their customers. It can be executed through one-to-one meetings telephonic marketing, digital marketing, and advertisement.

Despite of different methods, telephonic marketing is most convinient to communicate with customers. But this method needs large amount of money as call centers are involved to execute these campaigns. Hence, it is very important to identity the customers before head so that they can be particularly targeted through call.

This dataset is about the direct marketing campaign (phone calls) of Portuguese bank with a classification goal to examine the customers subscription behavior.

Intended Audiences:

This dataset is beneficial to the marketing manager and digital marketing manager of the bank. They can review and identify their potential customer for their term deposit plan.

1.1 Purpose

The main purpose of the project is to carry out an in-dept analysis to find the potential customers from data provided by the marketing campaign. For this we will answer some of the question among which some are listed below:

-Which type of job holders should we focus for more subscribition of term deposit by the customers?

-Which type of education background has subcribed more deposit of the bank?

-Why some factors like age,education background of customers affect whether customer subscribes term deposit?

1.2 Importance

This project is important because it provides bank with insights which will help them to make better decisions for increment of term deposit.

1.3 Brief Summary:

Using different analysis we found that the following behaviour of people subscribes more term deposit:

1. People with higher education background.
2. People with no housing or personal loan.
3. People with age from 30-50.

Also, using logistic regression, we concluded that the model correctly predicted 82.5 percent of cases.

2.(a) Understanding the data

In [2]:

```
#Importing the required libraries
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
plt.rc("font", size=18)
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
import gc
```

In [3]:

```
#reading the dataset using pandas library
df = pd.read_csv("banking.csv",delimiter=";")
#inside the read_csv("banking.csv",delimeter=";")
#"banking.csv" is the dataset.
#delimeter is used to form the column of the raw csv data
```

2.(b) Data Cleaning and data processing

Data Cleaning:

Data cleaning is the process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table or database and refers to identifying incomplete,incorrect, inaccurate or irrelevants parts of the data and then replacing,modifying or deleting the dirty or coarse data.

Data processing

Data processing is manipulation of data by a computer. It includes the conversion of raw data to machine-readable form, flow of data through the CPU and memory to output devices, and formatting or transformation of output. Any use of computers to perform defined operations on data can be included under data processing

For our project, the following Data cleaning and processing is being conducted:

1. We looked to see whether any "Missing or Null" values were present. There were no Null values in our data set.
2. Created new field named "number of people" to find the percentage with total.
3. Created new field name "percentage" that gives the rate with total subscription or not subscription in details with loan.

In [4]:
```
df['education'].unique() # checking the unique data of column education
```

Out[4]:
```
array(['tertiary', 'secondary', 'unknown', 'primary'], dtype=object)
```

In [5]:
```
df['y'].value_counts() # Calculate the dataset result of yes and no
```

Out[5]:
```
no     39922
yes     5289
Name: y, dtype: int64
```

In [6]:
```
# Determining the null value if any.
df.isnull().sum()
```

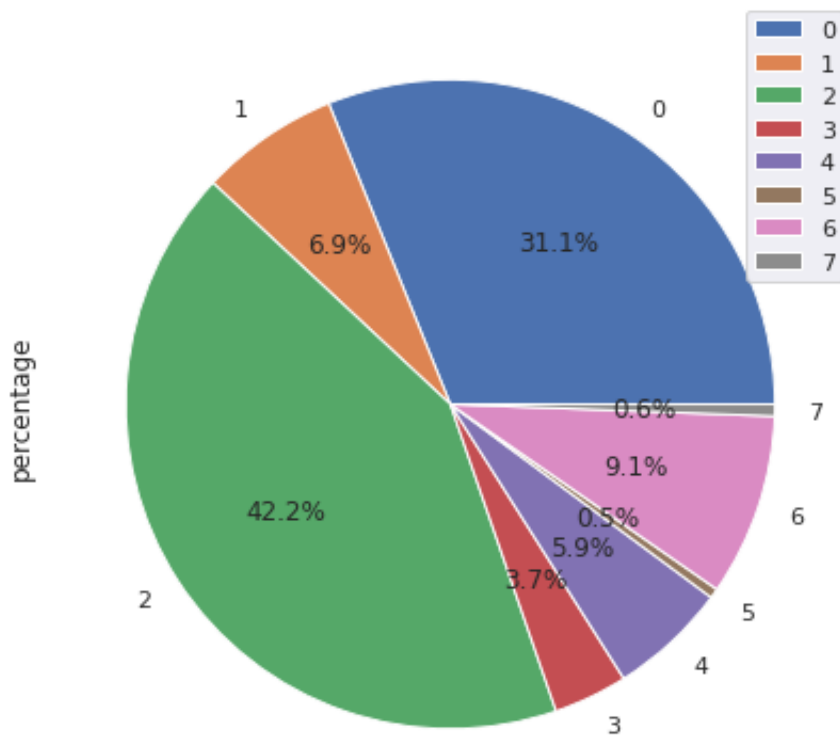
Out[6]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

There were no any null values or missing values in our dataset

In [48]:
```
# Creating the table for personal loan and housingloan in "Loan with y analys
df_loan = df.groupby(['loan','housing','y']).count()
df_loan = df_loan.reset_index()
df_loan_new = df_loan.loc[:,['loan','housing','y','age']]
df_loan_new.rename(columns={'loan': 'Housing Loan', 'housing': 'Personal Loan
                            'y':'Subscribe term deposit','age':'number of peo
df_loan_new["percentage"] = df_loan_new["number of people"] / sum(df_loan_new
df_loan_new.plot.pie(y = 'percentage',autopct='%2.1f%%',figsize=(7, 7))
df_loan_new
```

Out[48]:

	Housing Loan	Personal Loan	Subscribe term deposit	number of people	percentage
0	no	no	no	14069	31.118533
1	no	no	yes	3135	6.934153
2	no	yes	no	19093	42.230873
3	no	yes	yes	1670	3.693791
4	yes	no	no	2658	5.879100
5	yes	no	yes	219	0.484395
6	yes	yes	no	4102	9.073013
7	yes	yes	yes	265	0.586141



2.(c) Description of dataset

Below listed is the name of field along with their description in our dataset.

S.N	Name of Field	Description of field	Sub-Category
1	age	Age	Positive Integer
2	job	Type of Job	admin,unknown,unemployed,management,housemaid,enterpreneur,student,blue-collar,self-employed,retired,technician, services.
3	marital	Marital Status	married, divorced,single: divorced means divorced or widowed.
4	education	Educaation background	secondary, primary, tertiary,unknown
5	default	Has credit in default?	Yes or No
6	balance	average yearly balance	Amount in euros
7	housing	Has housing loan?	Yes or No
8	loan	Has personal loan?	Yes or No
9	contact	Contact Communication Type	Telephone, cellular,unknown.
10	day	Last contact day of month	in days.
11	month	Last contact month of year	jan,feb,mar,...nov,december
12	duration	Last contact duration in seconds	seconds
13	campaign	Number of contacts performed during this campaign and for this client	Numeric,includes last contact
14	pdays	Number of days that passed by after the client was last contacted from a previous campaign	numeric, -1 means client was not previously contacted
15	previous	Number of contacts performed before this campaign and	Numeric
16	poutcome	Outcome of previous marketing campaign	Unknown, failure,success,other
17	y	Has the client subscribed a term deposit?	Yes or No

In [8]:

```
print((df.columns))  # find the header of column in our dataset
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

In [9]:

```
# Finding the data types of our fields
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

2.(d) Basic descriptive features of the data

For our project we have selected direct marketing campaign (phone calls) of Portuguese bank. In our dataset we have 45211 number of rows and 17 number of columns. There are both categorical features data field (such as: "job", "marital", "education", "default","contact" "housing", "loan", "poutcome", "y","month) and numerical features data field (such as :age", "balance", "duration", "campaign", "pdays", "previous","day")

In [10]:

```
print(df.shape)  # find the shape of the dataset
print(df) # printing the dataset
```

```
(45211, 17)
       age           job   marital  education default  balance housing loan  \
0       58    management   married   tertiary      no     2143     yes   no   
1       44    technician    single  secondary      no       29     yes   no   
2       33  entrepreneur   married  secondary      no        2     yes  yes   
3       47   blue-collar   married    unknown      no     1506     yes   no   
4       33       unknown    single    unknown      no        1      no   no   
...    ...           ...       ...        ...     ...      ...     ...  ...   
45206   51    technician   married   tertiary      no      825      no   no   
45207   71       retired  divorced    primary      no     1729      no   no   
45208   72       retired   married  secondary      no     5715      no   no   
45209   57   blue-collar   married  secondary      no      668      no   no   
45210   37  entrepreneur   married  secondary      no     2971      no   no   

         contact  day month  duration  campaign  pdays  previous poutcome    y  
0        unknown    5   may       261         1     -1         0  unknown   no  
1        unknown    5   may       151         1     -1         0  unknown   no  
2        unknown    5   may        76         1     -1         0  unknown   no  
3        unknown    5   may        92         1     -1         0  unknown   no  
4        unknown    5   may       198         1     -1         0  unknown   no  
...          ...  ...   ...       ...       ...    ...       ...      ...  ...  
45206   cellular   17   nov       977         3     -1         0  unknown  yes  
45207   cellular   17   nov       456         2     -1         0  unknown  yes  
45208   cellular   17   nov      1127         5    184         3  success  yes  
45209  telephone   17   nov       508         4     -1         0  unknown   no  
45210   cellular   17   nov       361         2    188        11    other   no  

[45211 rows x 17 columns]
```

2.(e) Analysis and Explanation

A. Descriptive Analysis

Descriptive analysis will be used to better understand the data and identify the variables influencing the y(whether customer will subscribe term deposit).

Descriptive analytics is the interpretation of historical data to better understand changes that have occurred in a business. Descriptive analytics describes the use of a range of historic data to draw comparisons.

In this project via the discriptive analysis we will find the type of people who have suscribe the term deposit during the marketing campaign and provide the summary statistic of the profile of banking customers through the measure of central tendency(mean,median and mode). We will understand the effect of various factors on final result i.e. on whether customer will subscribe term deposit.

Data Expolaration

In [11]:
```
#attribute frequency
df_freq = df['y'].value_counts()
print(df_freq)
```

```
no     39922
yes     5289
Name: y, dtype: int64
```

In [12]:
```
#creating a new data frame for pie chart
keys = df_freq.keys()
print(keys)
```

```
Index(['no', 'yes'], dtype='object')
```

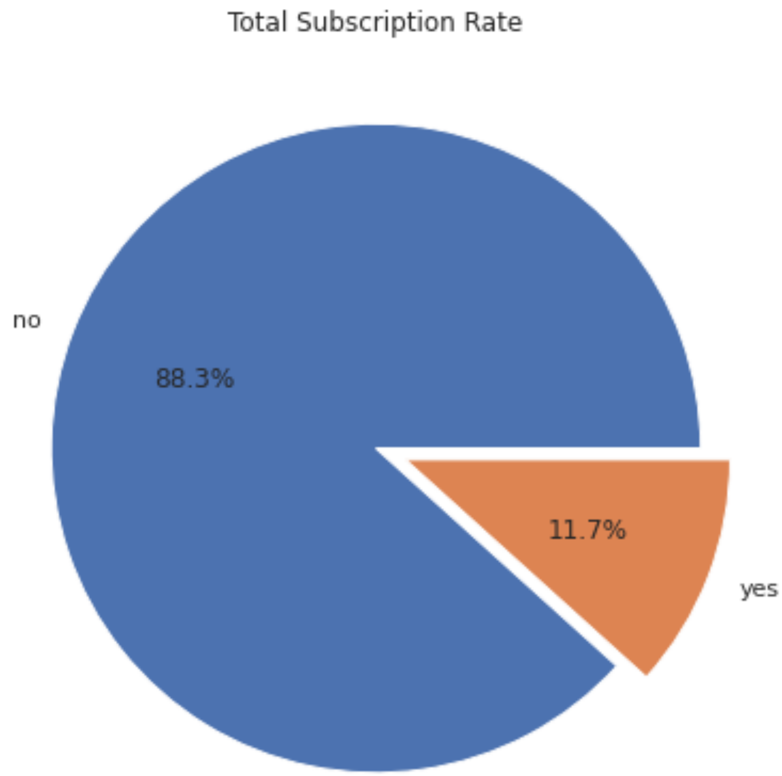
In [13]:
```
value = df_freq.values
print(value)
```

```
[39922  5289]
```

In [14]:
```
df2 = pd.DataFrame({"Subscribes":keys,"Total Numbers":value})
print(df2)
```

```
  Subscribes  Total Numbers
0         no          39922
1        yes           5289
```

In [63]:
```
#pie chat to show the attribute percentage
plt.pie(df2['Total Numbers'],labels=df2['Subscribes'],autopct='%2.1f%%',explo
plt.title("Total Subscription Rate")
fig = plt.gcf()
fig = fig.set_size_inches(7,7)
```



In total, only 11.7% of the customer contacted has subscribe the term deposit.

In [16]:
```
df.groupby('y').mean() # grouping all the numerical values and finding mean w
```

Out[16]:

y	age	balance	day	duration	campaign	pdays	previous
no	40.838986	1303.714969	15.892290	221.182806	2.846350	36.421372	0.502154
yes	41.670070	1804.267915	15.158253	537.294574	2.141047	68.702968	1.170354

From this we can conclude that:

-Customers who purchased term deposits are on average older than those who did not.

-For customers who purchased term deposit, the duration (last contact duration, in seconds) is higher. The higher the duration, the more discussion of bank products and, as a result, the higher the chances of a sale

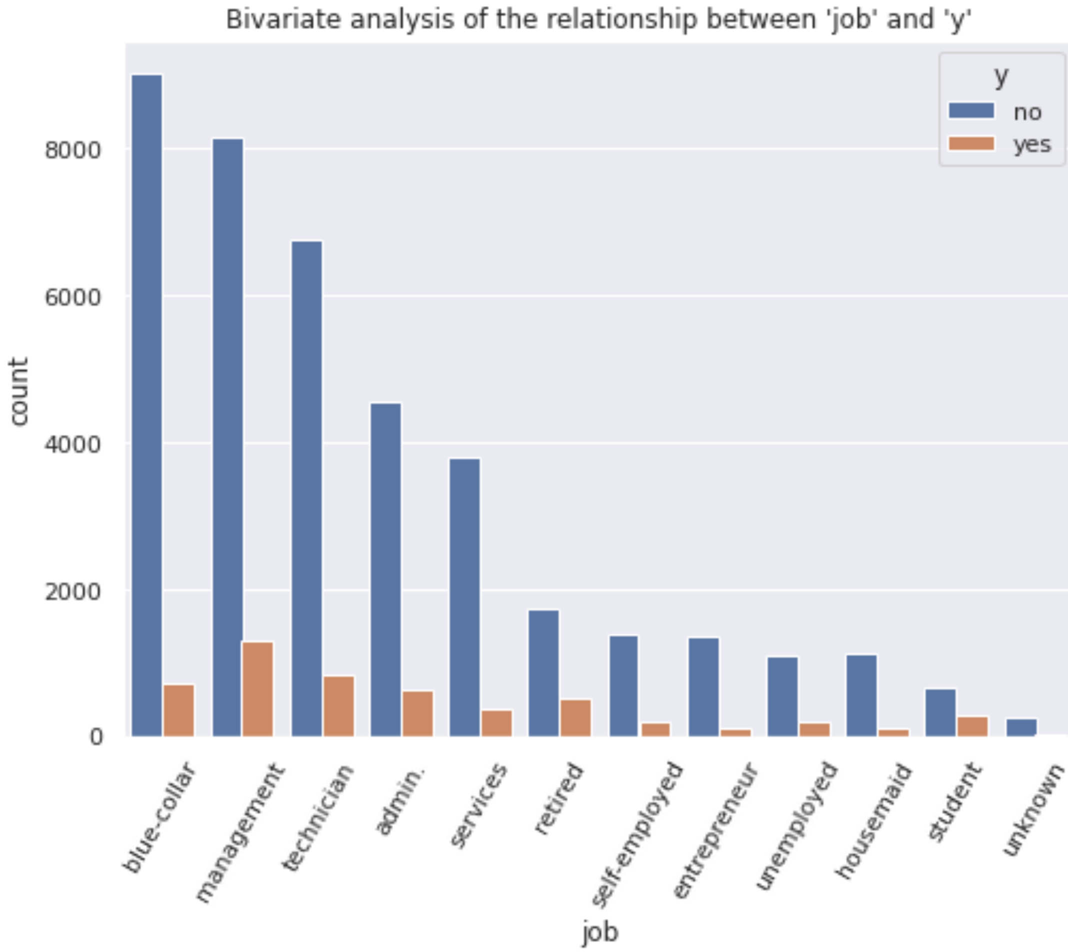
-Amazingly, campaigns (the number of contacts or calls made during the campaign) are lower for term deposit customers

Studying the various varibales and their effect on "y"

2.(e)(i) Job feature and y

In [17]:

```
# using seaborn library
#Bivariate analysis of the relationship between 'job' and 'y'
sns.set_theme(style='darkgrid') # theme set
sns.set(rc = {'figure.figsize':(8, 6)}) # assiging the figure size
job = sns.countplot(x="job", data = df, hue = "y", order = df["job"].value_co
job.tick_params(axis='x', rotation=60) # giving axis
plt.title("Bivariate analysis of the relationship between 'job' and 'y'") # g
plt.show()  # showing the figure
```



The bank focused its efforts on people with professional backgrounds. In comparison to others, most of term deposit takers have a high qualification.

In [18]:
```
df.groupby('job').mean() # grouping all the numerical values and finding mean
```

Out[18]:

job	age	balance	day	duration	campaign	pdays	previou
admin.	39.289886	1135.838909	15.564301	246.896732	2.575324	47.859021	0.67163
blue-collar	40.044081	1078.826654	15.442561	262.901562	2.816995	44.033498	0.50513
entrepreneur	42.190989	1521.470074	15.702085	256.309348	2.799597	32.486214	0.47814
housemaid	46.415323	1392.395161	16.002419	245.825000	2.820968	21.505645	0.37177
management	40.449567	1763.616832	16.114189	253.995771	2.864348	38.665468	0.66800
retired	61.626767	1984.215106	15.439488	287.361307	2.346731	37.443905	0.63869
self-employed	40.484484	1647.970868	16.027866	268.157061	2.853072	34.747308	0.55161
services	38.740250	997.088108	15.635532	259.318729	2.718344	41.995185	0.50120
student	26.542644	1388.060768	14.897655	246.656716	2.299574	57.041578	0.95309
technician	39.314598	1252.632092	16.408582	252.904962	2.906805	37.195077	0.57456
unemployed	40.961627	1521.745971	15.498081	288.543361	2.432080	34.146585	0.46661
unknown	47.593750	1772.357639	14.642361	237.611111	3.309028	20.982639	0.31944

From the above table we can see the different job title having means of different fields such as age, balance, day, duration, campaign, pdays, previous.

2.(e)(ii) Marital Status and y

In [19]:

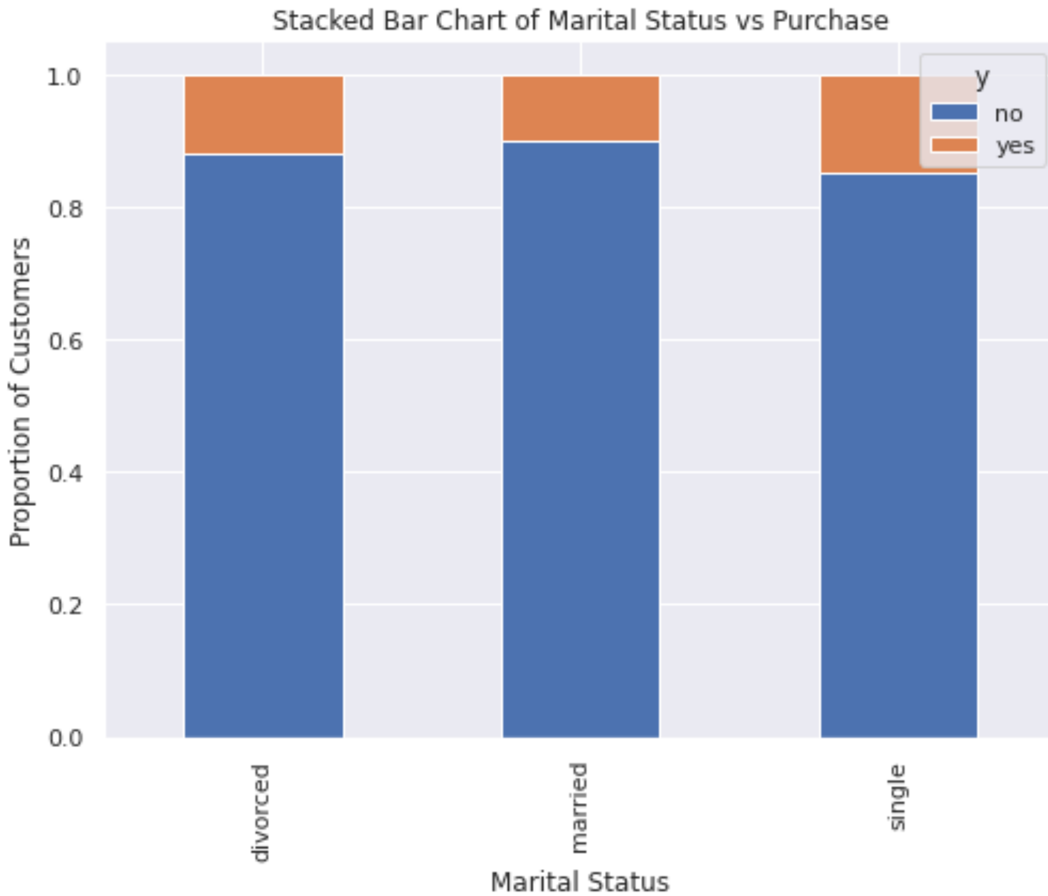
```
df.groupby('marital').mean() # grouping all the numerical values and finding
```

Out[19]:

marital	age	balance	day	duration	campaign	pdays	previous
divorced	45.782984	1178.872287	15.796428	262.517188	2.630882	41.001728	0.551373
married	43.408099	1425.925590	15.854487	253.412765	2.842875	37.950467	0.556552
single	33.703440	1301.497654	15.708210	266.497967	2.649805	44.652385	0.642690

In [20]:
```
# using the pandas library
# Stacked Bar Chart of Marital Status vs Purchase
table=pd.crosstab(df.marital,df.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Marital Status vs Purchase')
plt.xlabel('Marital Status')
plt.ylabel('Proportion of Customers')
```

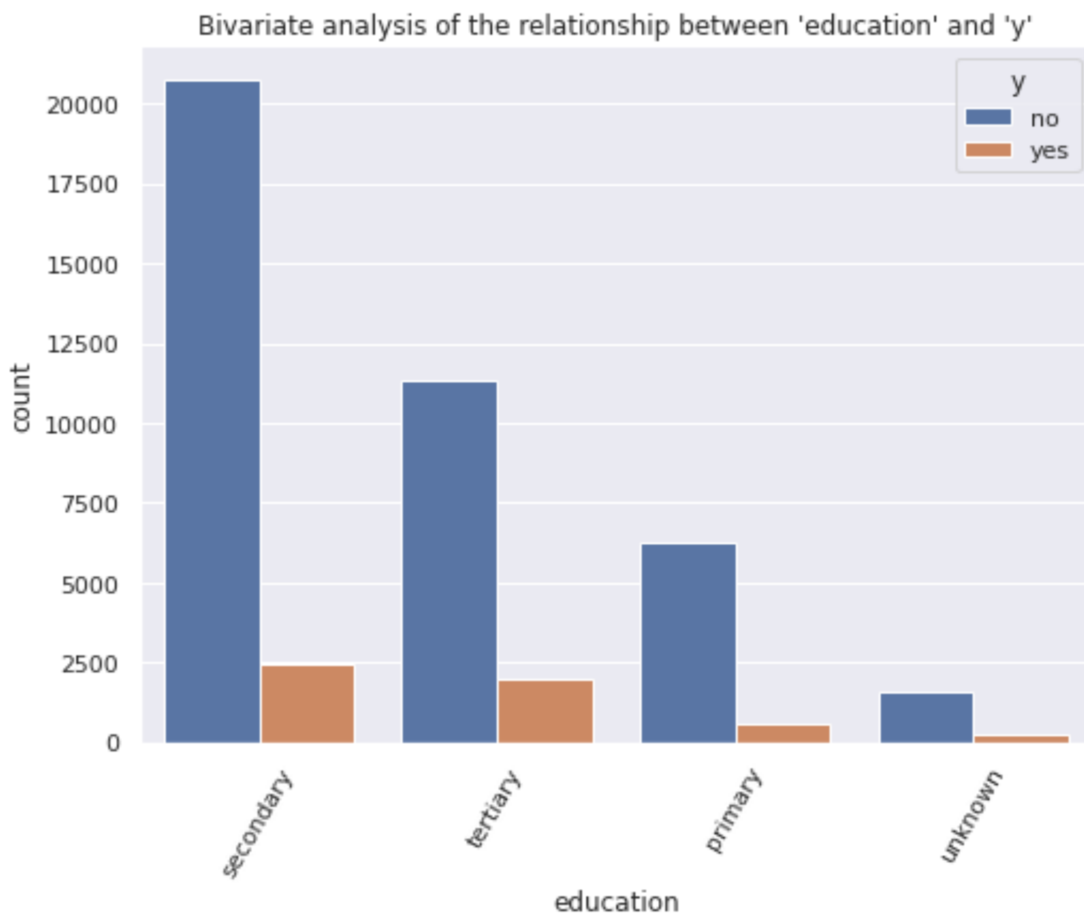
Out[20]:
```
Text(0, 0.5, 'Proportion of Customers')
```



The marital status does not appear to be a significant predictor of the outcome variable because the percentage of people who subscribed term deposit is almost same in every marital status with respect to their numbers.

2.(e)(iii) Education and y

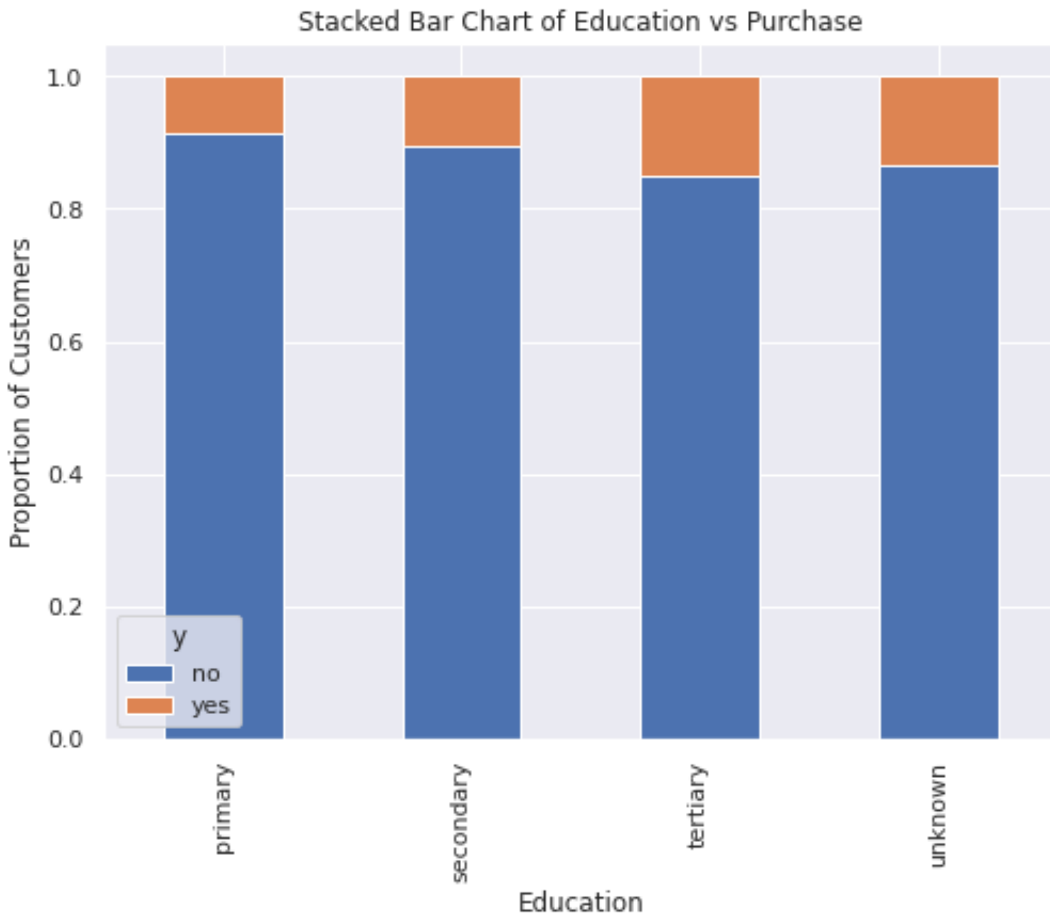
In [21]:
```
# Bivariate analysis of the relationship between 'education' and 'y'
sns.set_theme(style='darkgrid')
sns.set(rc = {'figure.figsize':(8, 6)})
education = sns.countplot(x="education", data = df, hue = "y", order = df["ed
education.tick_params(axis='x', rotation=60)
plt.title("Bivariate analysis of the relationship between 'education' and 'y'
plt.show()
```



As shown in the above chat we can analyze that people having secondary qualifications have subscribe more term deposit in terms of numbers.

In [22]:
```
# Stacked Bar Chart of Education vs Purchase
table=pd.crosstab(df.education,df.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Education vs Purchase')
plt.xlabel('Education')
plt.ylabel('Proportion of Customers')
```

Out[22]: Text(0, 0.5, 'Proportion of Customers')



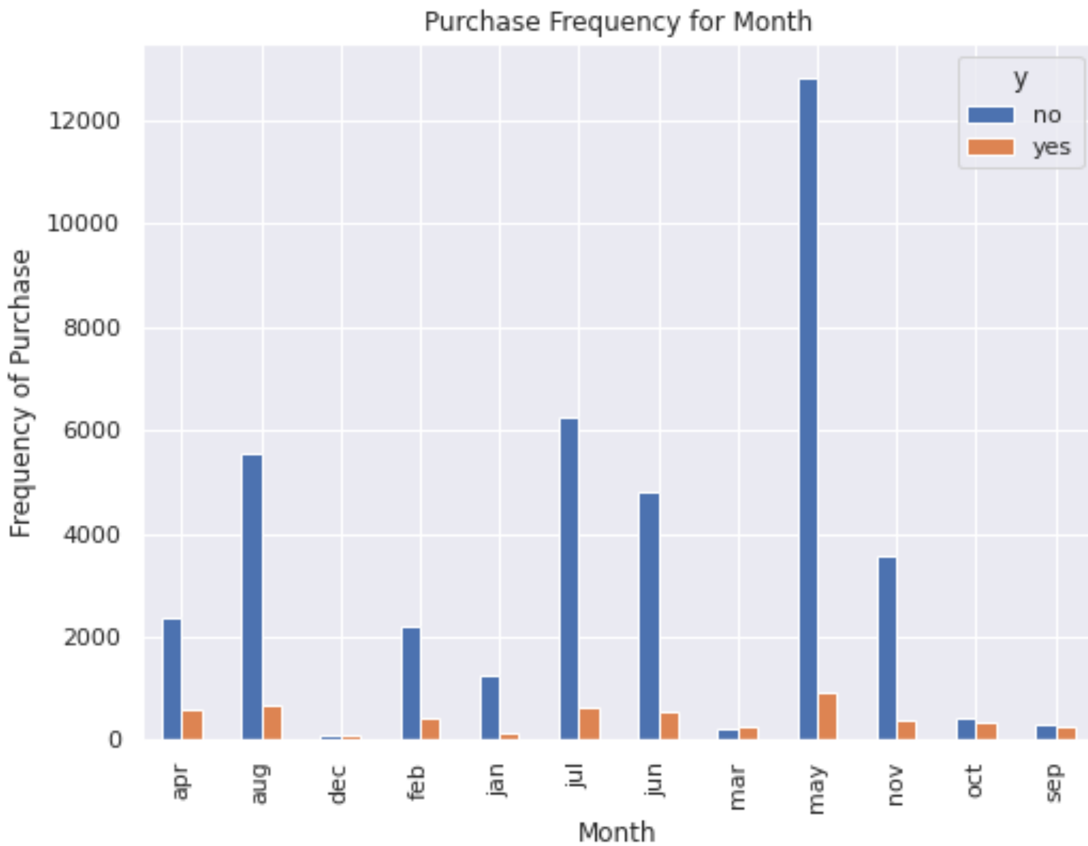
From figure "Bivariate analysis of the relationship between 'education' and y", we see that the number of people with secondary education background has subscribed more term deposit. However, from above figure we can conclude that people having tertiary education has subscribed more percentage of the term deposit in respect with their numbers.

2.(e)(iv) Month and y

In [23]:

```
# Bar chart of Purchase Frequency for Month
pd.crosstab(df.month,df.y).plot(kind='bar')
plt.title('Purchase Frequency for Month')
plt.xlabel('Month')
plt.ylabel('Frequency of Purchase')
```

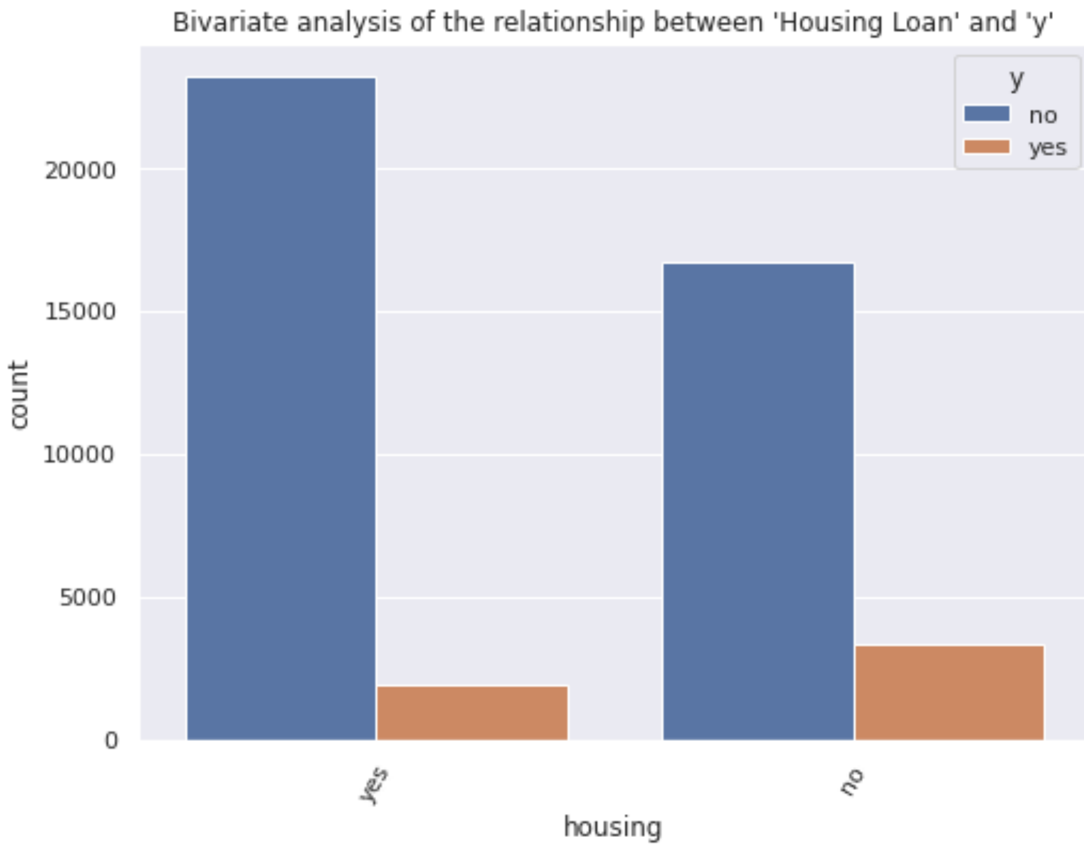
Out[23]:
```
Text(0, 0.5, 'Frequency of Purchase')
```



May had a slightly higher number of subscribers than the other months. Exception of December and January, the subscription average is nearly the same regardless of how many people are contacted. These were the months with the fewest subscriptions. One possible explanation is that people go on vacation. (People in the Americas are accustomed to taking vacations during this time of year.) Because the plot shows a proportional distribution of "yes," the "month" feature will be removed because it has no effect on the outcome.

2.(e)(v)Loan and y

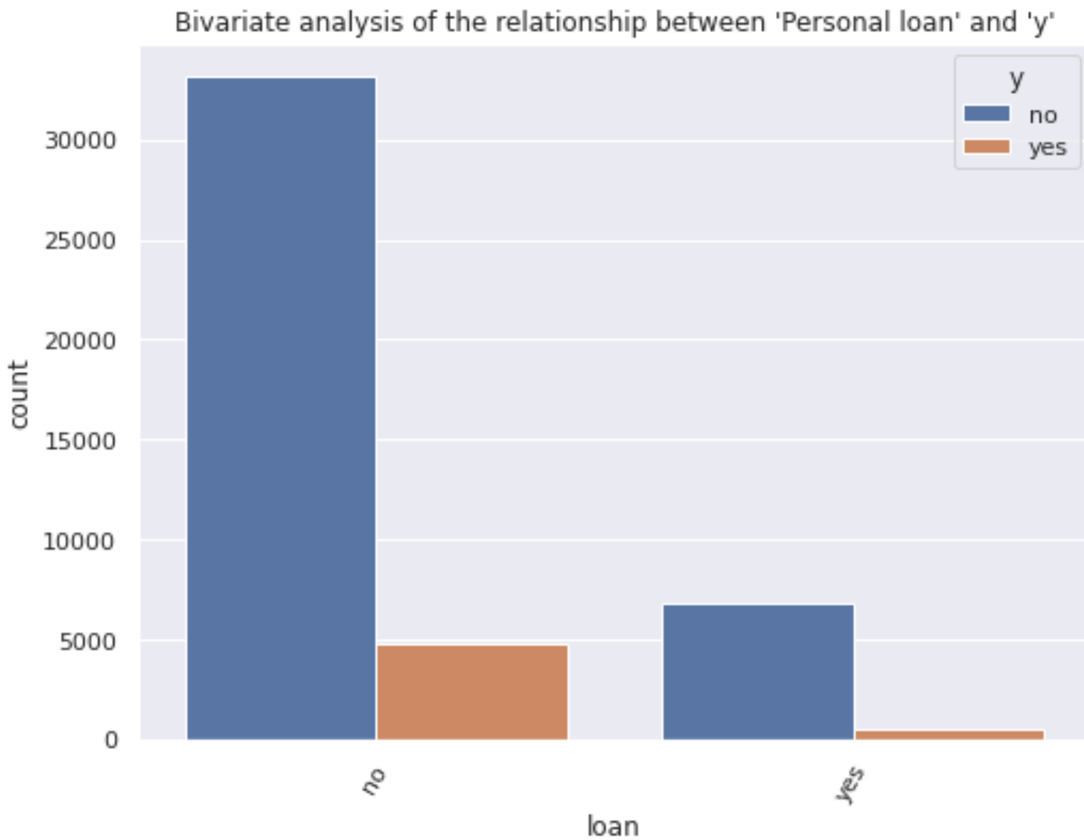
In [44]:
```
# Bivariate analysis of the relationship between 'Housing Loan' and 'y'
sns.set_theme(style='darkgrid')
sns.set(rc = {'figure.figsize':(8, 6)})
housing = sns.countplot(x="housing", data = df, hue = "y", order = df["housin
housing.tick_params(axis='x', rotation=60)
plt.title("Bivariate analysis of the relationship between 'Housing Loan' and
plt.show()
```



People who do not have a housing loan are more likely to subscribe for more term deposit.

In [45]:

```
# Bivariate analysis of the relationship between 'Personal loan' and 'y'
sns.set_theme(style='darkgrid')
sns.set(rc = {'figure.figsize':(8, 6)})
loan = sns.countplot(x="loan", data = df, hue = "y", order = df["loan"].value_
loan.tick_params(axis='x', rotation=60)
plt.title("Bivariate analysis of the relationship between 'Personal loan' and
plt.show()
```



People who did not have a personal loan, were willing to accept a more deposit term than with the people having personal loan.

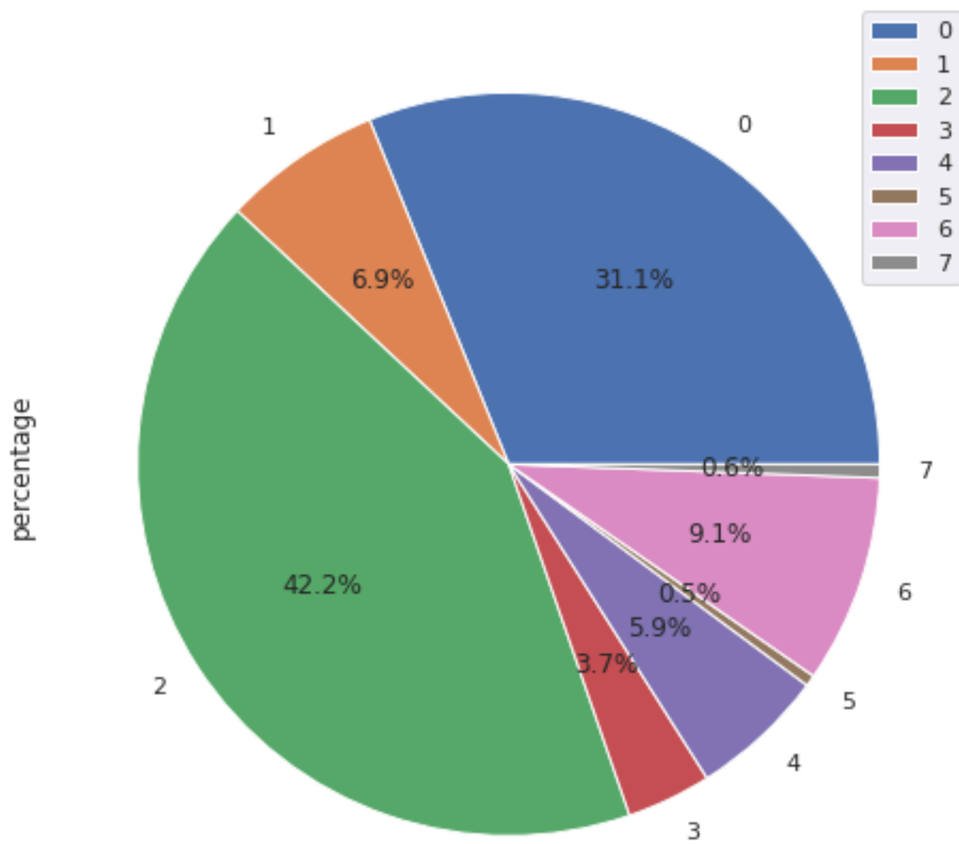
Also, it is observed that people with personal loan subscribed higher proportion of term deposit than with people having housing loan.

In [26]:

```
# creating the table for personal loan and housingloan
df_loan = df.groupby(['loan','housing','y']).count()
df_loan = df_loan.reset_index()
df_loan_new = df_loan.loc[:,['loan','housing','y','age']]
df_loan_new.rename(columns={'loan': 'Housing Loan', 'housing': 'Personal Loan
                            'y':'Subscribe term deposit','age':'number of peo
df_loan_new["percentage"] = df_loan_new["number of people"] / sum(df_loan_new
df_loan_new.plot.pie(y = 'percentage',autopct='%2.1f%%',figsize=(8, 8))
df_loan_new
```

Out[26]:

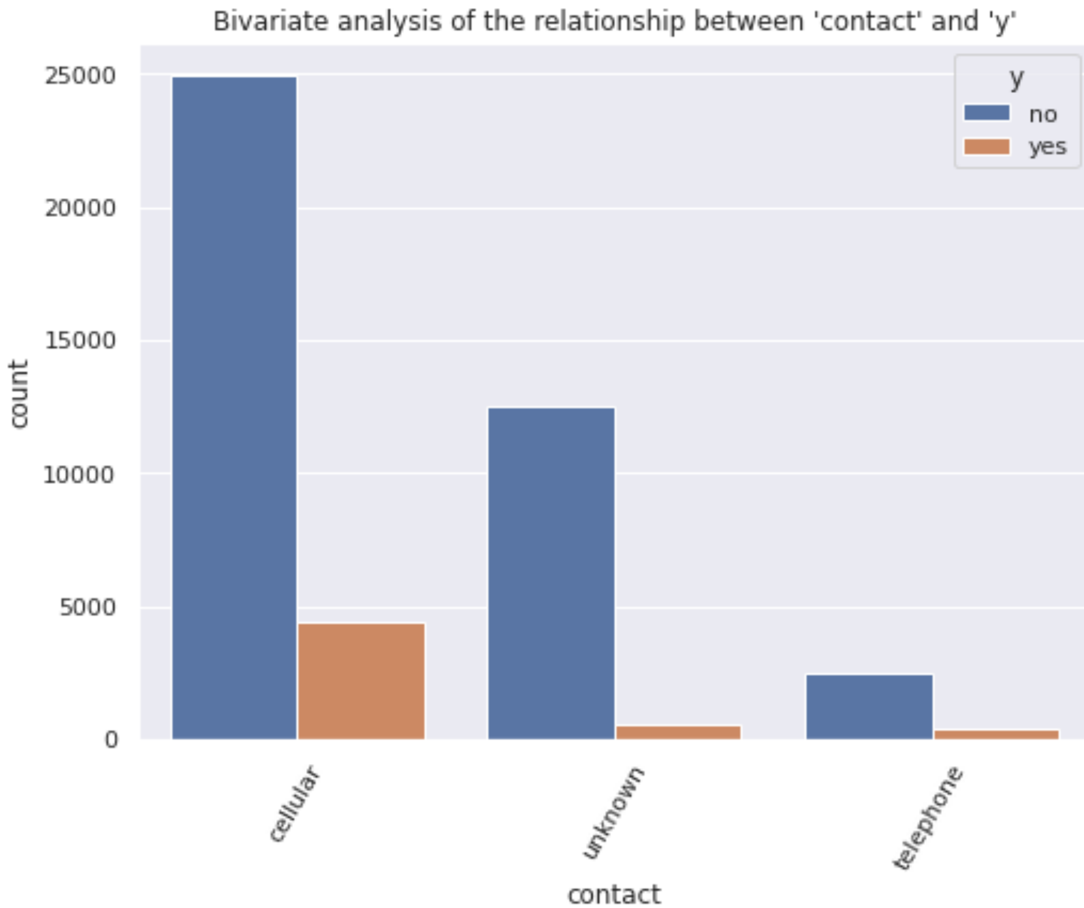
	Housing Loan	Personal Loan	Subscribe term deposit	number of people	percentage
0	no	no	no	14069	31.118533
1	no	no	yes	3135	6.934153
2	no	yes	no	19093	42.230873
3	no	yes	yes	1670	3.693791
4	yes	no	no	2658	5.879100
5	yes	no	yes	219	0.484395
6	yes	yes	no	4102	9.073013
7	yes	yes	yes	265	0.586141



Above 1,3,5,7 shows the percent of people who subscribe the term deposit and their sum is equal to 11.70%.

2.(e)(vi) Contact and y

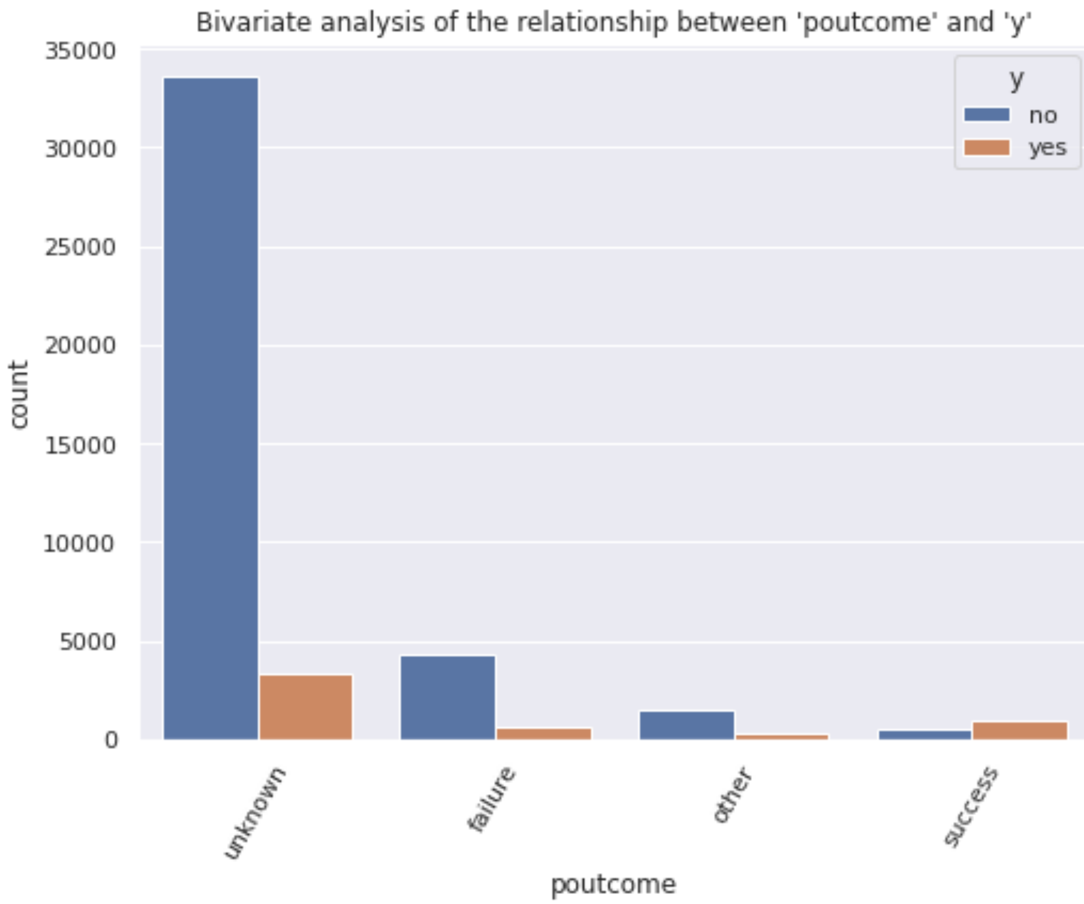
In [46]:
```
# Bivariate analysis of the relationship between 'contact' and 'y'
sns.set_theme(style='darkgrid')
sns.set(rc = {'figure.figsize':(8, 6)})
contact = sns.countplot(x="contact", data = df, hue = "y", order = df["contac
contact.tick_params(axis='x', rotation=60)
plt.title("Bivariate analysis of the relationship between 'contact' and 'y'")
plt.show()
```



The direct ratio in this graph shows that people who were contacted by cellular phone were more likely to sign up for a deposit term.

2.(e)(vii) poutcome feature and y

In [47]:
```
# Bivariate analysis of the relationship between 'poutcome' and 'y'
sns.set_theme(style='darkgrid')
sns.set(rc = {'figure.figsize':(8, 6)})
poutcome = sns.countplot(x="poutcome", data = df, hue = "y", order = df["pout
poutcome.tick_params(axis='x', rotation=60)
plt.title("Bivariate analysis of the relationship between 'poutcome' and 'y'"
plt.show()
```

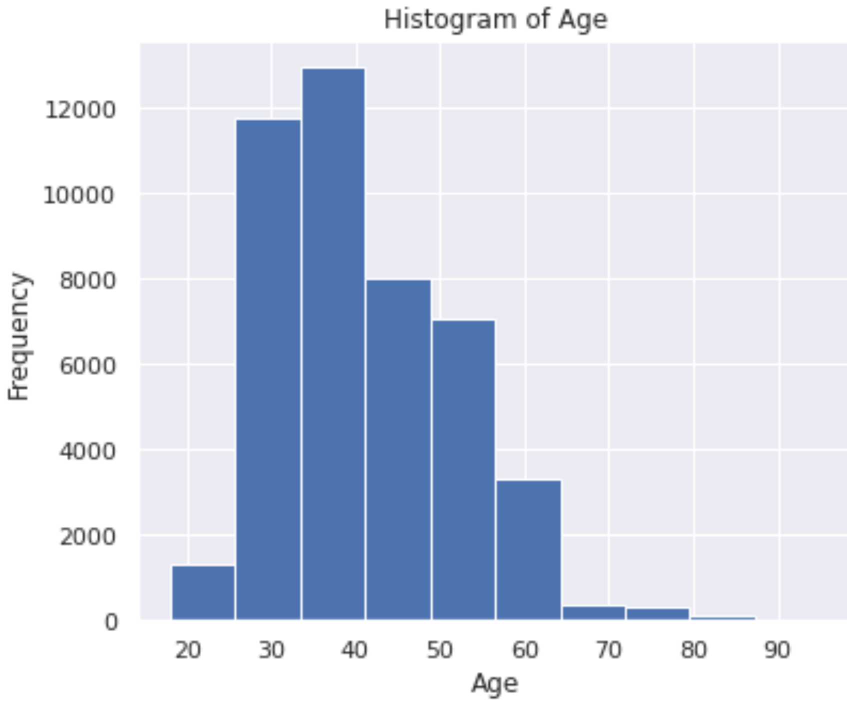


This one corresponds to the outcome of the previous marketing campaign's success. What exactly does "unknown" mean? This means that 78.7 percent of those contacted were unaware of the previous marketing campaign. This campaign's effort could have a positive impact on the previous campaign. "Success" has a very low percentage, but it is important for the analysis.

2.(e)(viii) Age and y

In [29]:

```
# Histogram of Age
df.age.hist()
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('hist_age')
```



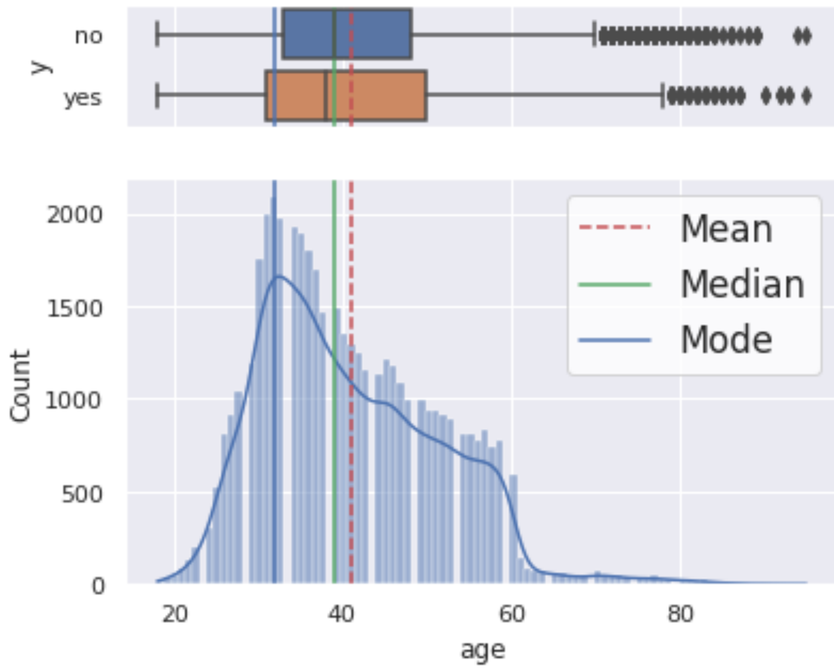
The majority of the bank's customers in this dataset are between the ages of 30 and 50.

In [30]:

```
# histogram of age and y
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_rat
sns.set(rc={'figure.figsize':(11,8)}, font_scale=1.5, style='whitegrid')
mean=df['age'].mean()
median=df['age'].median()
mode=df['age'].mode().values[0]

age = sns.boxplot(data=df, x="age", y="y", ax=ax_box, order = df["y"].value_c
# age.set(xscale="log")
ax_box.axvline(mean, color='r', linestyle='--')
ax_box.axvline(median, color='g', linestyle='-')
ax_box.axvline(mode, color='b', linestyle='-')

sns.histplot(data=df, x="age", ax=ax_hist, kde=True)
ax_hist.axvline(mean, color='r', linestyle='--', label="Mean")
ax_hist.axvline(median, color='g', linestyle='-', label="Median")
ax_hist.axvline(mode, color='b', linestyle='-', label="Mode")
ax_hist.legend()
ax_box.set(xlabel='')
plt.show()
```



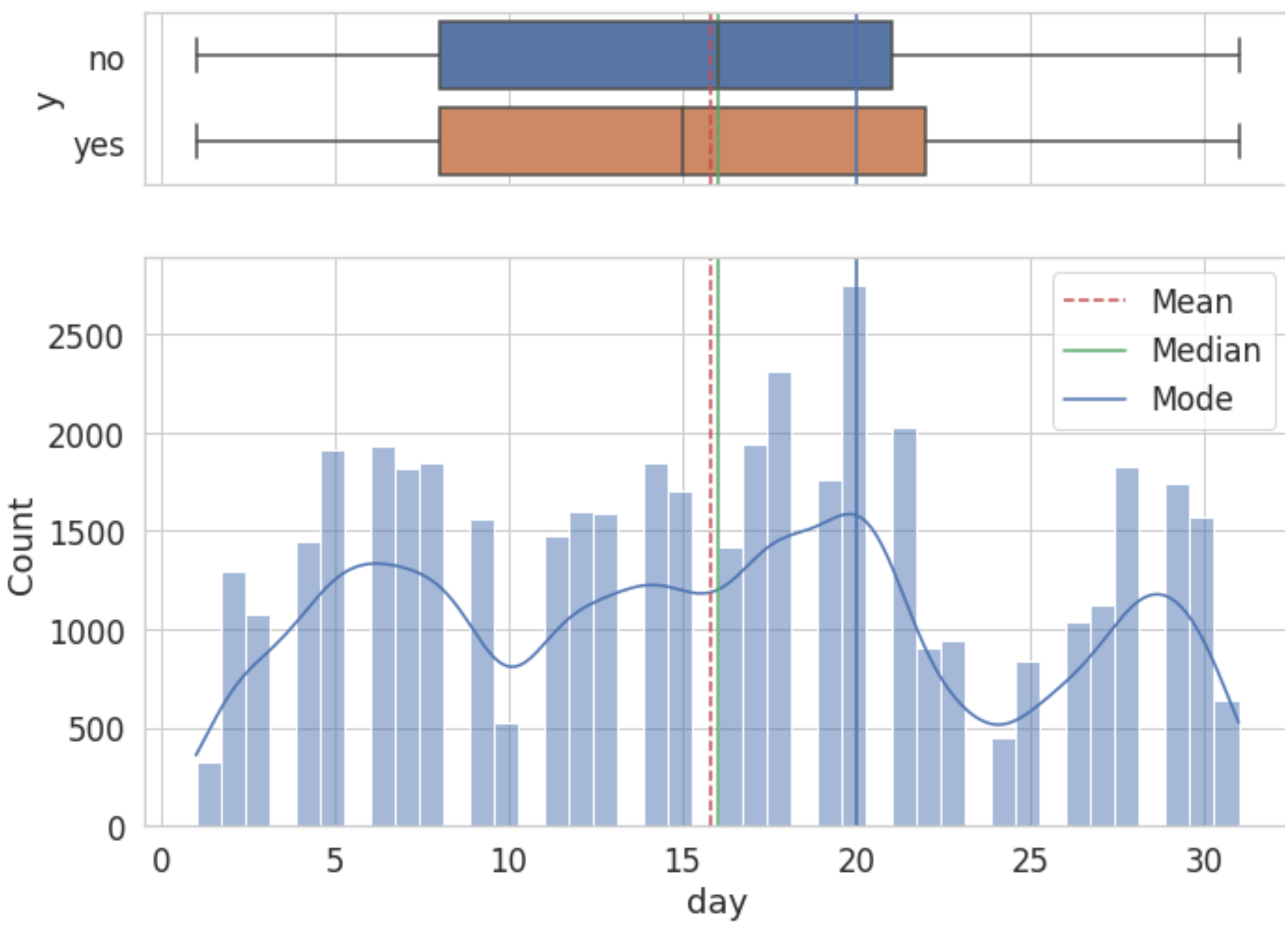
Using a box visual representation, this function depicts the relationship between "age" and the categorical target variable. Furthermore, the histogram displays a bell-shaped image with a left-shifted normal distribution, as shown below. The population ranges from 20 to 60 years old. The box plot depicts a specific age group between 30 and 50. Probably because this is when people are more productive and stable. When we consider the job feature, this trend becomes stronger. Bivariate analysis is useful because it shows the call center that they need to target a specific segment of customers.

2.(e)(ix) Day Feature and y

In [31]:
```
# histogram of day feature and y
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_rat
sns.set(rc={'figure.figsize':(11,8)}, font_scale=1.5, style='whitegrid')
mean=df['day'].mean()
median=df['day'].median()
mode=df['day'].mode().values[0]

day = sns.boxplot(data=df, x="day", y="y", ax=ax_box, order = df["y"].value_c
# age.set(xscale="log")
ax_box.axvline(mean, color='r', linestyle='--')
ax_box.axvline(median, color='g', linestyle='-')
ax_box.axvline(mode, color='b', linestyle='-')

sns.histplot(data=df, x="day", ax=ax_hist, kde=True)
ax_hist.axvline(mean, color='r', linestyle='--', label="Mean")
ax_hist.axvline(median, color='g', linestyle='-', label="Median")
ax_hist.axvline(mode, color='b', linestyle='-', label="Mode")
ax_hist.legend()
ax_box.set(xlabel='')
plt.show()
```



The histogram exhibits symmetry across the entire data set, with a peak on day 20. This feature will be removed from the dataset analysis because it makes no significant contribution to the outcome. Plots show that people can sign up on any day of the week.

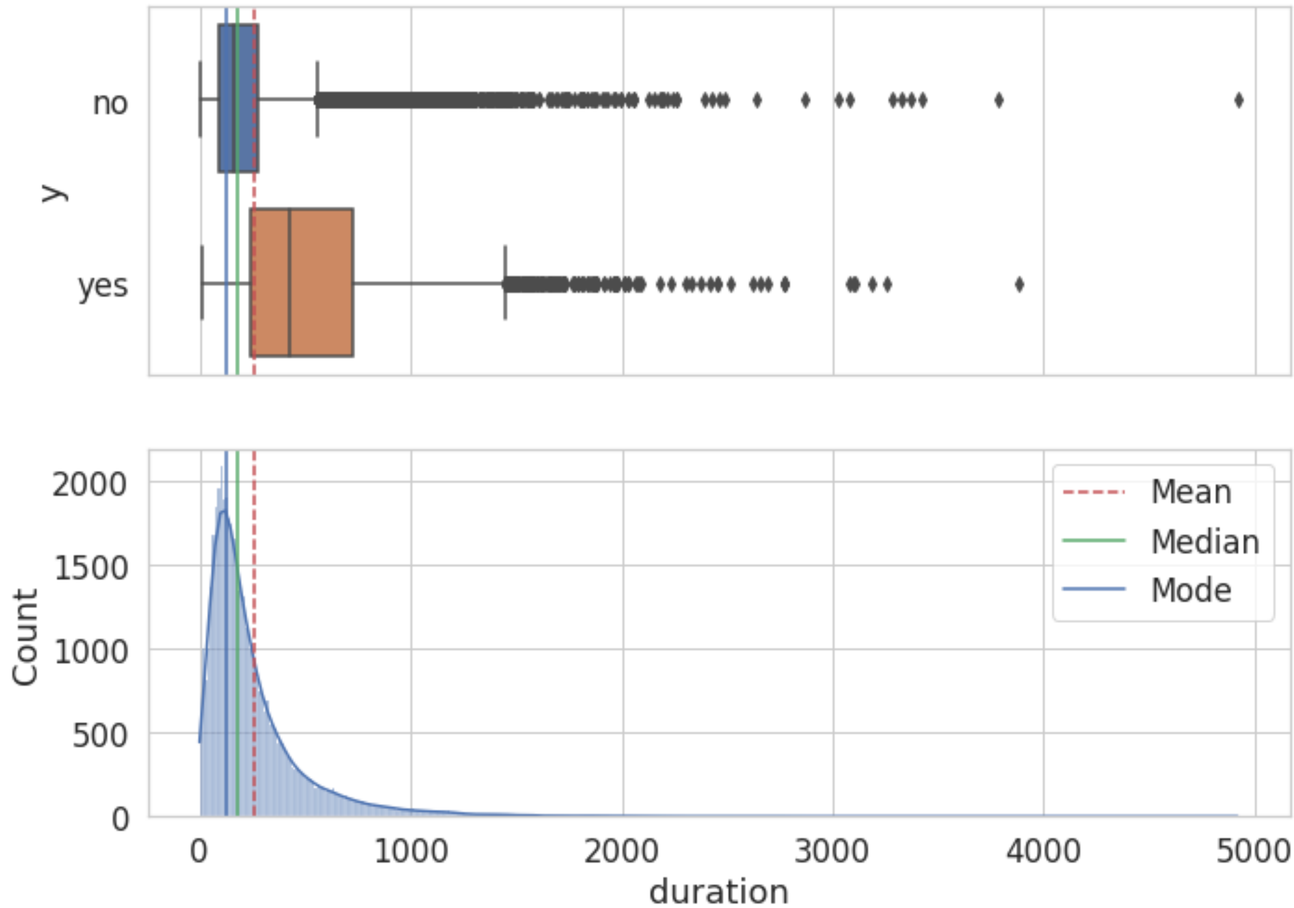
2.(e)(x) Duration Feature and y

In [32]:

```
# Histogram of durtion feature and y
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True) # gridspec_kw= {"height_r
sns.set(rc={'figure.figsize':(11,8)}, font_scale=1.5, style='whitegrid')
mean=df['duration'].mean()
median=df['duration'].median()
mode=df['duration'].mode().values[0]

duration = sns.boxplot(data=df, x="duration", y="y", ax=ax_box, order = df["y
# age.set(xscale="log")
ax_box.axvline(mean, color='r', linestyle='--')
ax_box.axvline(median, color='g', linestyle='-')
ax_box.axvline(mode, color='b', linestyle='-')

sns.histplot(data=df, x="duration", ax=ax_hist, kde=True)
ax_hist.axvline(mean, color='r', linestyle='--', label="Mean")
ax_hist.axvline(median, color='g', linestyle='-', label="Median")
ax_hist.axvline(mode, color='b', linestyle='-', label="Mode")
ax_hist.legend()
ax_box.set(xlabel='')
plt.show()
```



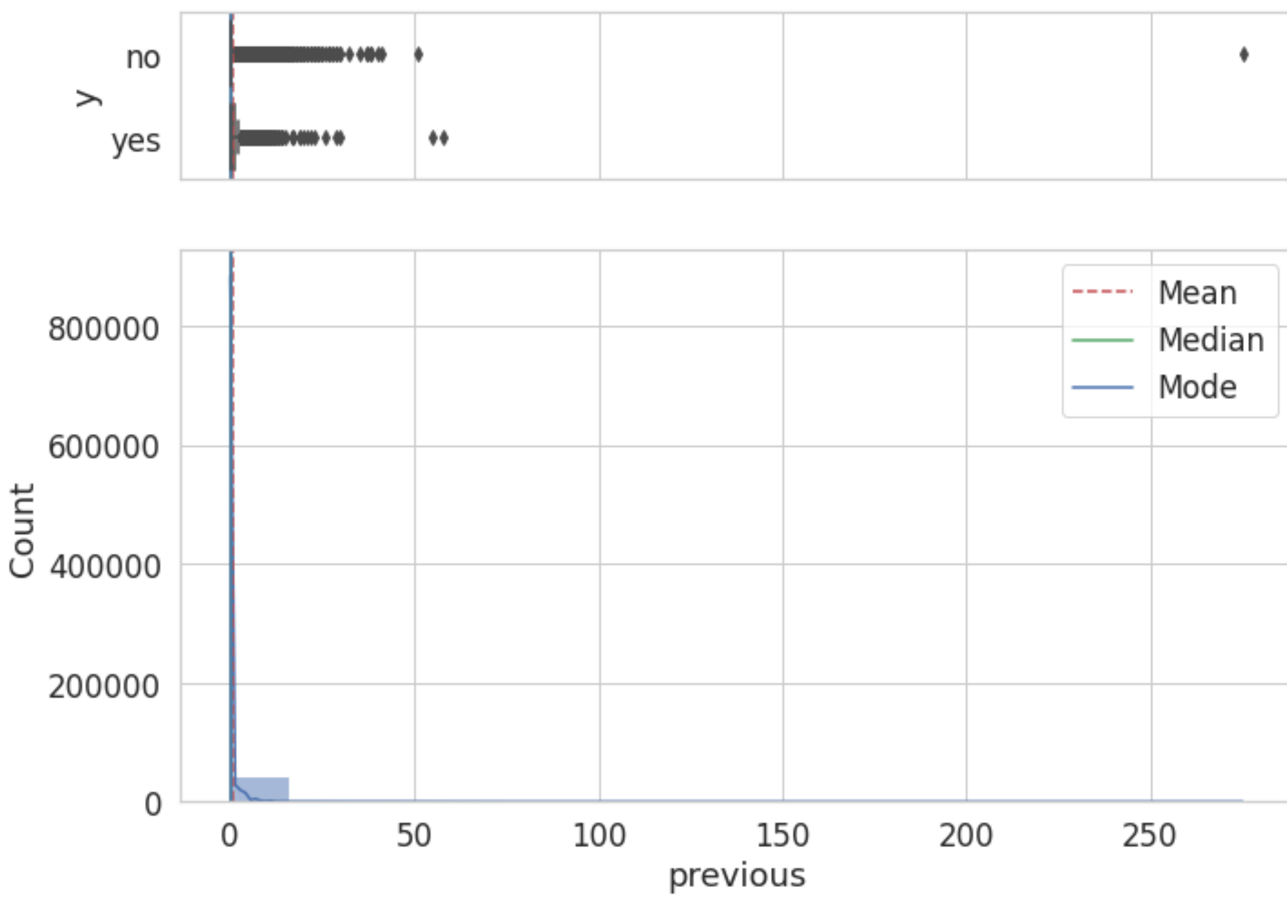
Duration feature influences the "y" result. We can see in the graph below that when the duration is between 0 and the first two minutes, most of people reject the offer. The remanent samples decide in a time span ranging from more than 2 minutes to 12 minutes. Only a few people take a long time to reject or accept an offer.

2.(e)(xi)Previous and y

In [33]:
```
# histogram of previous and y
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_rat
sns.set(rc={'figure.figsize':(10,7)}, font_scale=1.5, style='whitegrid')
mean=df['previous'].mean()
median=df['previous'].median()
mode=df['previous'].mode().values[0]

previous = sns.boxplot(data=df, x="previous", y="y", ax=ax_box, order = df["y
# age.set(xscale="log")
ax_box.axvline(mean, color='r', linestyle='--')
ax_box.axvline(median, color='g', linestyle='-')
ax_box.axvline(mode, color='b', linestyle='-')

sns.histplot(data=df, x="previous", ax=ax_hist, kde=True)
ax_hist.axvline(mean, color='r', linestyle='--', label="Mean")
ax_hist.axvline(median, color='g', linestyle='-', label="Median")
ax_hist.axvline(mode, color='b', linestyle='-', label="Mode")
ax_hist.legend()
ax_box.set(xlabel='')
plt.show()
```



"previous" refers to the number of contacts made prior to this campaign and for this client. As shown below, 36954 belong to the 0 group. This means that 36954 people were contacted for the first time for this campaign. Furthermore, the box-plot is missing; it does not show a distribution, indicating that there is no relationship with the target. It will also be removed from the analysis.

B. Diagnostic Analysis

Diagnostic analytics is a type of advanced analytics that examines data or content to answer the question “why did it happen?”.

Diagnostic analytics takes a deeper look at data to better understand the causes of behaviors and events, to help answer critical workforce questions.

We want to understand the observation from the Descriptive Analysis more thoroughly in Diagnostic Analysis.

The major factor affecting the subscription of term deposit according to our studies are:

1. Age group of people
2. Education background of people

With the above fields the following Regression Analysis is performed to support our hypothesis.

Evidences and Hypothesis:

Evidences:

According to GoBankingRates' annual saving survey in 2018 almost 43% of personal savings is kept in bank in forms of checking accounts, savings account and certificate of deposit. While the rest of savings are invested in 401k (employers sponsored defined contribution pension account),physical assets (home, car, etc) etc. So, it means that there is positive relationship between personal savings and term deposits.

Thus we can say that there is direct positive relationship between personal savings and term deposits.

A positive association between a good education background and savings has been suggested in a number of articles. According to study,[Knueven,L,Business Insider] she has mentioned that education affects the saving balance (according to Survey of Consumer Finances) as below:

Highesh education level completed	Average savings balance
No high school diploma	$7,600
High school diploma	$16,700
Some college	$18,900
College degree	$85,600

Moreover, according to article by [Perez,L,valuepenguin] that mentioned data collected from Federal Reserve in 2019, the individual with a college degree are more likely to have a higher bank account balance as below:

Highesh education level completed	Average bank balance
College degree	$79,100
Some college	$23,500
High School diploma	$20,100
No high school diploma	$9,300

Also, according to article by [Perez,L,valuepenguin] that mentioned that olders individuals are likely to have higher balances in their savings accounts as below:

Age	Average bank balance
Under 35	$11,200
35-44	$27,900
45-54	$48,200
55-64	$57,800
65-74	$60,400

So from the above articles we can conclude that:

Hypothesis 1 : There is significant positive relationship between education background and bank balance.

Hypothesis 2: There is significant positive relationship between age and bank balance.

C. Predictive Analysis

Since, our dependent varibale is "Categorical" varibale, OLS (Ordinary Regression Model) wont be good fit . We use the Logistic Regression to better understand our prediction and ensure that the Analysis we performed is accurate.

Logistic Regression:

It is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, the logistic regression is a predictive analysis. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

Sometimes logistic regressions are difficult to interpret; the Intellectus Statistics tool easily allows you to conduct the analysis, then in plain English interprets the output.

We will be able to receive the percentage amount of prediction for the Model below. In other words, the Model's output will tell us how accurate our analysis is and how well we can anticipate the values.

In [34]:

```
train = pd.read_csv("train.csv", sep=';')
test = pd.read_csv("test.csv.xls", sep=';')
train_copy = train.copy()
test_copy = test.copy()
# Set up a flag to distinguish records in the concatenated dataset
train_copy['tst'] = 0
test_copy['tst'] = 1

# Concatenate train and test dataset to perform pre-prepocessing
train_test_concat = pd.concat([train_copy, test_copy], ignore_index=True)
del train_copy
del test_copy
gc.collect()

print(train_test_concat.shape)
print(train.shape)
print(test.shape)
```

```
(49732, 18)
(45211, 17)
(4521, 17)
```

In [35]:
```
# a. Replace method: Mode value
train_test_concat["job"].replace(["unknown"],train_test_concat["job"].mode(),
train_test_concat["education"].replace(["unknown"],train_test_concat["educati
train_test_concat["contact"].replace(["unknown"],train_test_concat["contact"]
```

In [36]:
```
# b. Drop unrepresentative features
train_test_concat.drop(columns = ["month", "previous", "day", "pdays"], inpla
print(train_test_concat)
```

```
       age           job  marital education default  balance housing loan  \
0       58    management  married  tertiary      no     2143     yes   no
1       44    technician   single secondary      no       29     yes   no
2       33  entrepreneur  married secondary      no        2     yes  yes
3       47   blue-collar  married secondary      no     1506     yes   no
4       33   blue-collar   single secondary      no        1      no   no
...    ...           ...      ...       ...     ...      ...     ...  ...
49727   33      services  married secondary      no     -333     yes   no
49728   57 self-employed  married  tertiary     yes    -3313     yes  yes
49729   57    technician  married secondary      no      295      no   no
49730   28   blue-collar  married secondary      no     1137      no   no
49731   44  entrepreneur   single  tertiary      no     1136     yes  yes

        contact  duration  campaign poutcome   y  tst
0      cellular       261         1  unknown  no    0
1      cellular       151         1  unknown  no    0
2      cellular        76         1  unknown  no    0
3      cellular        92         1  unknown  no    0
4      cellular       198         1  unknown  no    0
...         ...       ...       ...      ...  ..  ...
49727  cellular       329         5  unknown  no    1
49728  cellular       153         1  unknown  no    1
49729  cellular       151        11  unknown  no    1
49730  cellular       129         4    other  no    1
49731  cellular       345         2    other  no    1

[49732 rows x 14 columns]
```

In [37]:
```
# a. Encoding categorical features.
train_test_concat['default'] = train_test_concat['default'].map({'yes': 1, 'n
train_test_concat['housing'] = train_test_concat['housing'].map({'yes': 1, 'n
train_test_concat['loan'] = train_test_concat['loan'].map({'yes': 1, 'no': 0}
train_test_concat['contact'] = train_test_concat['contact'].map({'telephone':
train_test_concat['y'] = train_test_concat['y'].map({'yes': 1, 'no': 0})
train_test_concat
```

Out[37]:

	age	job	marital	education	default	balance	housing	loan	contact	duratio
0	58	management	married	tertiary	0	2143	1	0	0	2(
1	44	technician	single	secondary	0	29	1	0	0	1!
2	33	entrepreneur	married	secondary	0	2	1	1	0	7
3	47	blue-collar	married	secondary	0	1506	1	0	0	9
4	33	blue-collar	single	secondary	0	1	0	0	0	1!
...	...	...	...	...	...	...	...	...	...	
49727	33	services	married	secondary	0	-333	1	0	0	3:
49728	57	self-employed	married	tertiary	1	-3313	1	1	0	1!
49729	57	technician	married	secondary	0	295	0	0	0	1!
49730	28	blue-collar	married	secondary	0	1137	0	0	0	1:
49731	44	entrepreneur	single	tertiary	0	1136	1	1	0	3

49732 rows × 14 columns

In [38]:

```
# a. ['job', 'marital', 'education', 'poutcome'] are categorical variable tha

train_test_concat = pd.get_dummies(train_test_concat, columns=['job', 'marita
train_test_concat
```

Out[38]:

	age	default	balance	housing	loan	contact	duration	campaign	y	tst	...	marital
0	58	0	2143	1	0	0	261	1	0	0	...	
1	44	0	29	1	0	0	151	1	0	0	...	
2	33	0	2	1	1	0	76	1	0	0	...	
3	47	0	1506	1	0	0	92	1	0	0	...	
4	33	0	1	0	0	0	198	1	0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
49727	33	0	-333	1	0	0	329	5	0	1	...	
49728	57	1	-3313	1	1	0	153	1	0	1	...	
49729	57	0	295	0	0	0	151	11	0	1	...	
49730	28	0	1137	0	0	0	129	4	0	1	...	
49731	44	0	1136	1	1	0	345	2	0	1	...	

49732 rows × 31 columns

In [39]:

```
# Logistic Regression model for classification
# Training, Test, & Split
y = train_test_concat["y"]
X = train_test_concat.drop("y",axis = 1)

X_train , X_test , y_train , y_test = train_test_split(X, y, test_size = 0.4,

# Logistic Regression Model 1: The performance did not improve with data scal
logreg = LogisticRegression(solver='liblinear')
logreg.fit(X_train,y_train)
y_pred = logreg.predict(X_test)
```

In [40]:

```
# Logistic Regression model evaluation.
# Evaluation 1.
# importing required library
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import sklearn.metrics as metrics
from sklearn.model_selection import cross_val_score

print(confusion_matrix(y_pred, y_test))
print(classification_report(y_test, y_pred))
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
[[17226  1583]
 [  374   710]]
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     17600
           1       0.65      0.31      0.42      2293

    accuracy                           0.90     19893
   macro avg       0.79      0.64      0.68     19893
weighted avg       0.89      0.90      0.89     19893

Accuracy: 0.9016236867239733
```

In [41]:

```
##Oversampling. Overcoming imbalance problem
from imblearn.over_sampling import RandomOverSampler

ROS = RandomOverSampler(sampling_strategy='minority', random_state=1)

X_train_ROS, y_train_ROS = ROS.fit_resample(X_train, y_train)
np.bincount(y_train_ROS)
```

Out[41]:

```
array([26322, 26322])
```

In [42]:

```
# Second test of LR model with oversampling
logreg_oversampling = LogisticRegression(solver='liblinear')
logreg_oversampling.fit(X_train_ROS, y_train_ROS)
y_pred_oversampling = logreg_oversampling.predict(X_test)
```

In [43]:

```
# Evaluation 2.
print(confusion_matrix(y_pred_oversampling, y_test))
print(classification_report(y_test, y_pred_oversampling))
print("Accuracy:",metrics.accuracy_score(y_test, y_pred_oversampling))
```

```
[[14648   514]
 [ 2952  1779]]
              precision    recall  f1-score   support

           0       0.97      0.83      0.89     17600
           1       0.38      0.78      0.51      2293

    accuracy                           0.83     19893
   macro avg       0.67      0.80      0.70     19893
weighted avg       0.90      0.83      0.85     19893

Accuracy: 0.8257678580405168
```

Following conclusion can be made:

1. From above confusion_matrix in the output, 14,648 & 1,779 are actual predictions and 514 & 2,952 are in correct predictions.

2. Based on the accuracy analysis above, we can conclude that the model correctly predicted 82.5 percent of cases.

3. This demonstrated that the model properly projected attrition for 82.5 percent of term deposit subscriptions.

3. A.Conclusion

3.A1 Descriptive Analysis:

Finally, the main results of our Descriptive Analysis are as follows:

1. Approximately one-tenth (1/10) of customer contacted has subscribed the term deposit from marketing campaign.

2. Customers who purchased term deposits are on average older than those who did not.

3. For customers who purchased term deposit, the duration (last contact duration, in seconds) is higher.

4. Majority of customers who subscribed term deposit are highly qualified.

5. There is no relation between "Marital Status" and "Subcription of term deposit" as marital status doesn't have much more effect on customers subscribtion.
6. May had a slightly higher number of subscribers than the other months.
7. People with no housing loan and no personal loan are subscribing more to the term deposit plan.
8. The people who were contacted by cellular phone were more likely to sign up for a deposit term.
9. The majority of the bank's customers in this dataset are between the ages of 30 and 50.
10. The duration feature influences the "y" result. When the duration is between 0 and the first two minutes, most people reject the offer. The remanent samples decide in a time span ranging from more than 2 minutes to 12 minutes. Only a few people take a long time to reject or accept an offer.

3.A2 Diagnostic Analysis

As a consequence of our diagnostic investigation, we discovered that persons with better education backgrounds have more savings, which leads to more bank deposits.

3.A3 Predictive Analysis

We used Logistic Regression to forecast the accuracy percentage of our study because our Regression Model was not a good fit. We estimate that our model is accurate up to 82.5 percent based on the results. This means that we can forecast client subscriptions for 82.5 percent of the whole population.

The management may currently forecast a term deposit subscription rate of 82.5 percent

3.A4 Prescriptive Analysis

The Management is now in a position to :

1. Determine the potential targeted clients based on a variety of characteristics such as age and educational background.
2. Apply corrective actions to the banking marketing and figure out why people aren't signing up for the term deposit plan.
3. For upcoming promotions, management can identify potential clients by categorical identification and provide a corrective action plan.

3.B Business Implication for audiences

The Hypothesis considered for our study was -

Hypothesis 1: There is significant positive relationship between education background and bank balance.

Hypothesis 2: There is significant positive relationship between age and bank balance.

According to our findings we were able to conduct that "Hypothesis 1: There is significant positive relationship between education background and bank balance." is the one of the key reasons the customers subscribes the term deposits. If the customers have high education background it is likely that they will subscribe more term deposits.

3.C Limitation of the Project

For our study, the dataset offered the following restriction.

1) "Subscription of term deposit" is the dependent variable, or the variable under our study. This variable's data is categorical rather than numerical. As a result, relying solely on multiple field to reach a conclusion proved difficult.

2) Our classes are unbalanced, with an 89:11 ratio of no-subscription instances to subscription instances. As a result, we'll need to perform oversampling on our dataset

3.D Future Potential

Complex algorithms and machine learning technologies can be utilized to examine and evaluate our dataset in order to accurately forecast the outcome. This allows management to fully comprehend the variables impacting decisions, such as the factors influencing client term deposit subscriptions

References

1. https://www.kaggle.com/prakharrathi25/banking-dataset-marketing-targets?select=test.csv
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9. https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/what-is-logistic-regression/
10. https://www.codecademy.com/articles/seaborn-design-i#:~:text=Seaborn%20has%20five%20built%2Din,better%20suit%20your%20presentation%
11. https://datatofish.com/logistic-regression-python/
12. https://www.xplenty.com/blog/prescriptive-analytics/