Bank Telemarketing Campaign Case Study.

In this case study you'll be learning Exploratory Data Analytics with the help of a case study on "Bank marketing campaign". This will enable you to understand why EDA is a most important step in the process of Machine Learning.

Problem Statement:

The bank provides financial services/products such as savings accounts, current accounts, debit cards, etc. to its customers. In order to increase its overall revenue, the bank conducts various marketing campaigns for its financial products such as credit cards, term deposits, loans, etc. These campaigns are intended for the bank's existing customers. However, the marketing campaigns need to be cost-efficient so that the bank not only increases their overall revenues but also the total profit. You need to apply your knowledge of EDA on the given dataset to analyse the patterns and provide inferences/solutions for the future marketing campaign.

The bank conducted a telemarketing campaign for one of its financial products 'Term Deposits' to help foster long-term relationships with existing customers. The dataset contains information about all the customers who were contacted during a particular year to open term deposit accounts.

What is the term Deposit?

Term deposits also called fixed deposits, are the cash investments made for a specific time period ranging from 1 month to 5 years for predetermined fixed interest rates. The fixed interest rates offered for term deposits are higher than the regular interest rates for savings accounts. The customers receive the total amount (investment plus the interest) at the end of the maturity period. Also, the money can only be withdrawn at the end of the maturity period. Withdrawing money before that will result in an added penalty associated, and the customer will not receive any interest returns.

Your target is to do end to end EDA on this bank telemarketing campaign data set to infer knowledge that where bank has to put more effort to improve it's positive response rate.

Importing the libraries.

In [1]:

```
#import the warnings.
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#import the useful libraries.
import pandas as pd, numpy as np
import matplotlib.pyplot as plt, seaborn as sns
%matplotlib inline
```

Session- 2, Data Cleaning

Segment- 2, Data Types

There are multiple types of data types available in the data set. some of them are numerical type and some of categorical type. You are required to get the idea about the data types after reading the data frame.

Following are the some of the types of variables:

- **Numeric data type**: banking dataset: salary, balance, duration and age.
- **Categorical data type**: banking dataset: education, job, marital, poutcome and month etc.
- **Ordinal data type**: banking dataset: Age group.
- **Time and date type**
- **Coordinates type of data**: latitude and longitude type.

Read in the Data set.

In [3]:

```
#read the data set of "bank telemarketing campaign" in inp0.
inp0= pd.read_csv("bank_marketing_updated_v1.csv")
```

In [4]:

```
#Print the head of the data frame.
inp0.head()
```

Out[4]:

	banking marketing	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6
0	customer id and age.	NaN	Customer salary and balance.	NaN	Customer marital status and job with education level.	NaN	particular customer before targeted or not
1	customerid	age	salary	balance	marital	jobedu	targeted
2	1	58	100000	2143	married	management,tertiary	yes
3	2	44	60000	29	single	technician,secondary	yes
4	3	33	120000	2	married	entrepreneur,secondary	yes

Segment- 3, Fixing the Rows and Columns

Checklist for fixing rows:

- **Delete summary rows**: Total and Subtotal rows
- **Delete incorrect rows**: Header row and footer row

- **Delete extra rows**: Column number, indicators, Blank rows, Page No.

Checklist for fixing columns:

- **Merge columns for creating unique identifiers**, if needed, for example, merge the columns State and City into the column Full address.
- **Split columns to get more data**: Split the Address column to get State and City columns to analyse each separately.
- **Add column names**: Add column names if missing.
- **Rename columns consistently**: Abbreviations, encoded columns.
- **Delete columns**: Delete unnecessary columns.
- **Align misaligned columns**: The data set may have shifted columns, which you need to align correctly.

Read the file without unnecessary headers.

In [5]:

```
#read the file in inp0 without first two rows as it is of no use.
inp0=pd.read_csv("bank_marketing_updated_v1.csv", skiprows= 2)
```

In [6]:

```
#print the head of the data frame.
inp0.head()
```

Out[6]:

	customerid	age	salary	balance	marital	jobedu	targeted	default	housi
0	1	58.0	100000	2143	married	management,tertiary	yes	no	y
1	2	44.0	60000	29	single	technician,secondary	yes	no	y
2	3	33.0	120000	2	married	entrepreneur,secondary	yes	no	y
3	4	47.0	20000	1506	married	blue-collar,unknown	no	no	y
4	5	33.0	0	1	single	unknown,unknown	no	no	

Dropping customer id column.

In [7]:

```
#drop the customer id as it is of no use.
inp0.drop("customerid", axis=1, inplace=True)
inp0.head()
```

Out[7]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan	c
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no	un
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no	un
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	un
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no	un
4	33.0	0	1	single	unknown,unknown	no	no	no	no	un

Dividing "jobedu" column into job and education categories.

In [8]:

```
#Extract job in newly created 'job' column from "jobedu" column.
inp0['job']=inp0.jobedu.apply(lambda x: x.split(",")[0])
inp0.head()
```

Out[8]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan	c
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no	un
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no	un
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	un
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no	un
4	33.0	0	1	single	unknown,unknown	no	no	no	no	un

In [9]:

```
#Extract education in newly created 'education' column from "jobedu" column.
inp0['education']=inp0.jobedu.apply(lambda x: x.split(",")[1])
inp0.head()
```

Out[9]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan	c
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no	un
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no	un
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	un
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no	un
4	33.0	0	1	single	unknown,unknown	no	no	no	no	un

In [10]:

```
#drop the "jobedu" column from the dataframe.
inp0.drop('jobedu',axis= 1, inplace= True)
inp0.head()
```

Out[10]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	du
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017	2
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017	1
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may, 2017	
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may, 2017	
4	33.0	0	1	single	no	no	no	no	unknown	5	may, 2017	1

Extract the month from column 'month'

In [11]:

```
inp0[inp0.month.apply(lambda x: isinstance(x,float))== True]
```

Out[11]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	mont
189	31.0	100000	0	single	no	no	yes	no	unknown	5	Na
769	39.0	20000	245	married	yes	no	yes	no	unknown	7	Na
860	33.0	55000	165	married	yes	no	no	no	unknown	7	Na
1267	36.0	50000	114	married	yes	no	yes	yes	unknown	8	Na
1685	34.0	20000	457	married	yes	no	yes	no	unknown	9	Na
...	...	...	...	...	...	...	...	...	...	...	.
43001	35.0	60000	353	single	no	no	no	no	cellular	11	Na
43021	52.0	100000	4675	married	yes	no	no	no	cellular	12	Na
43323	54.0	70000	0	divorced	yes	no	no	no	cellular	18	Na
44131	27.0	100000	843	single	yes	no	no	no	cellular	12	Na
44732	23.0	4000	508	single	no	no	no	no	cellular	8	Na

let's check the missing values in month column.

In [12]:

```
inp0.isnull().sum()
```

Out[12]:

```
age          20
salary        0
balance       0
marital       0
targeted      0
default       0
housing       0
loan          0
contact       0
day           0
month        50
duration      0
campaign      0
pdays         0
previous      0
poutcome      0
response     30
job           0
education     0
dtype: int64
```

Segment- 4, Impute/Remove missing values

Take aways from the lecture on missing values:

- **Set values as missing values**: Identify values that indicate missing data, for example, treat blank strings, "NA", "XX", "999", etc., as missing.
- **Adding is good, exaggerating is bad**: You should try to get information from reliable external sources as much as possible, but if you can't, then it is better to retain missing values rather than exaggerating the existing rows/columns.
- **Delete rows and columns**: Rows can be deleted if the number of missing values is insignificant, as this would not impact the overall analysis results. Columns can be removed if the missing values are quite significant in number.
- **Fill partial missing values using business judgement**: Such values include missing time zone, century, etc. These values can be identified easily.

Types of missing values:

- **MCAR**: It stands for Missing completely at random (the reason behind the missing value is not dependent on any other feature).
- **MAR**: It stands for Missing at random (the reason behind the missing value may be associated with some other features).
- **MNAR**: It stands for Missing not at random (there is a specific reason behind the missing value).

handling missing values in age column.

In [13]:

```
#count the missing values in age column.
inp0.age.isnull().sum()
```

Out[13]:

```
20
```

In [14]:

```
#pring the shape of dataframe inp0
inp0.shape
```

Out[14]:

```
(45211, 19)
```

In [15]:

```
#calculate the percentage of missing values in age column.
float(100.0*20/45211)
```

Out[15]:

```
0.04423702196368141
```

Drop the records with age missing.

In [16]:

```
#drop the records with age missing in inp0 and copy in inp1 dataframe.
inp1=inp0[-inp0.age.isnull()].copy()
inp1.shape
```

Out[16]:

```
(45191, 19)
```

handling missing values in month column

In [17]:

```
#count the missing values in month column in inp1.
inp1.month.isnull().sum()
```

Out[17]:

```
50
```

In [18]:

```
#print the percentage of each month in the data frame inp1.
float(100.0*50/45191)
```

Out[18]:

```
0.11064149941360005
```

In [19]:

```
inp1.month.value_counts(normalize = True)
```

Out[19]:

```
may, 2017    0.304380
jul, 2017    0.152522
aug, 2017    0.138123
jun, 2017    0.118141
nov, 2017    0.087880
apr, 2017    0.064908
feb, 2017    0.058616
jan, 2017    0.031058
oct, 2017    0.016327
sep, 2017    0.012760
mar, 2017    0.010545
dec, 2017    0.004741
Name: month, dtype: float64
```

In [20]:

```
#find the mode of month in inp1
month_mode=inp1.month.mode()[0]
month_mode
```

Out[20]:

```
'may, 2017'
```

In [21]:

```
# fill the missing values with mode value of month in inp1.
inp1.month.fillna(month_mode, inplace= True)
inp1.month.value_counts(normalize= True)
```

Out[21]:

```
may, 2017    0.305149
jul, 2017    0.152353
aug, 2017    0.137970
jun, 2017    0.118010
nov, 2017    0.087783
apr, 2017    0.064836
feb, 2017    0.058551
jan, 2017    0.031024
oct, 2017    0.016309
sep, 2017    0.012746
mar, 2017    0.010533
dec, 2017    0.004735
Name: month, dtype: float64
```

In [22]:

```
#let's see the null values in the month column.
inp1.month.isnull().sum()
```

Out[22]:

```
0
```

handling missing values in response column

In [23]:

```
#count the missing values in response column in inp1.
inp1.response.isnull().sum()
```

Out[23]:

```
30
```

In [24]:

```
#calculate the percentage of missing values in response column.
float(100.0*30/45191)
```

Out[24]:

```
0.06638489964816004
```

Target variable is better of not imputed.

- Drop the records with missing values.

In [25]:

```
#drop the records with response missings in inp1.
inp1= inp1[~inp1.response.isnull()]
```

In [26]:

```
#calculate the missing values in each column of data frame: inp1.
inp1.isnull().sum()
```

Out[26]:

```
age          0
salary       0
balance      0
marital      0
targeted     0
default      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
response     0
job          0
education    0
dtype: int64
```

handling pdays column.

In [27]:

```
#describe the pdays column of inp1.
inp1.pdays.describe()
```

Out[27]:

```
count    45161.000000
mean        40.182015
std        100.079372
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

-1 indicates the missing values. Missing value does not always be present as null. How to handle it:

Objective is:

- you should ignore the missing values in the calculations
- simply make it missing - replace -1 with NaN.
- all summary statistics- mean, median etc. we will ignore the missing values of pdays.

In [28]:

```
#describe the pdays column with considering the -1 values.
inp1.loc[inp1.pdays<0,"pdays"]=np.NaN
inp1.pdays.describe()
```

Out[28]:

```
count    8246.000000
mean      224.542202
std       115.210792
min         1.000000
25%       133.000000
50%       195.000000
75%       327.000000
max       871.000000
Name: pdays, dtype: float64
```

Segment- 5, Handling Outliers

Major approaches to the treat outliers:

- **Imputation**
- **Deletion of outliers**
- **Binning of values**
- **Cap the outlier**

Age variable

In [29]:

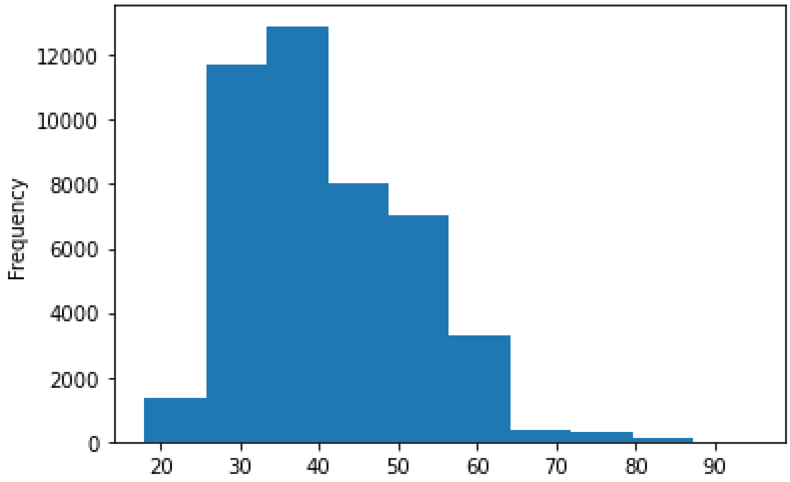
```
#describe the age variable in inp1.
inp1.age.describe()
```

Out[29]:

```
count    45161.000000
mean        40.935763
std         10.618790
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64
```

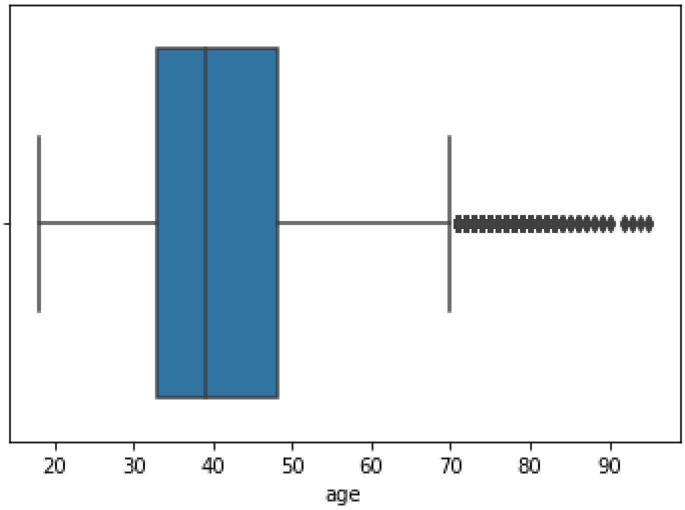
In [30]:

```
#plot the histogram of age variable.
inp1.age.plot.hist()
plt.show()
```



In [31]:

```
#plot the boxplot of age variable.
sns.boxplot(inp1.age)
plt.show()
```



Salary variable

In [32]:

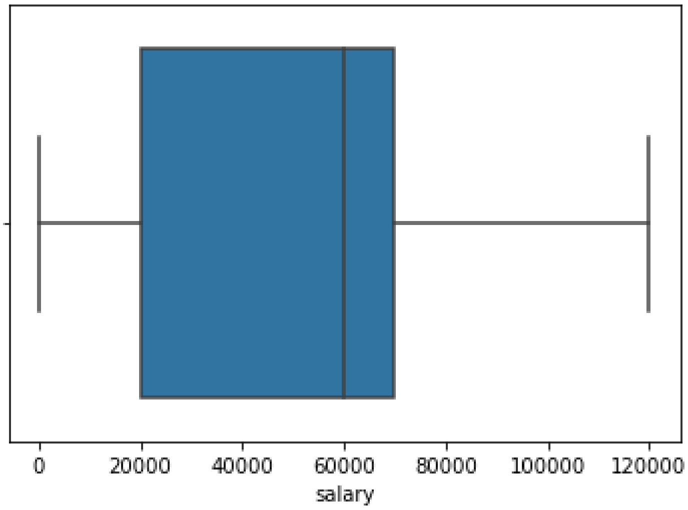
```
#describe the salary variable of inp1.
inp1.salary.describe()
```

Out[32]:

```
count     45161.000000
mean      57004.849317
std       32087.698810
min           0.000000
25%       20000.000000
50%       60000.000000
75%       70000.000000
max      120000.000000
Name: salary, dtype: float64
```

In [33]:

```
#plot the boxplot of salary variable.
sns.boxplot(inp1.salary)
plt.show()
```



Balance variable

In [34]:

```
#describe the balance variable of inp1.
inp1.balance.describe()
```

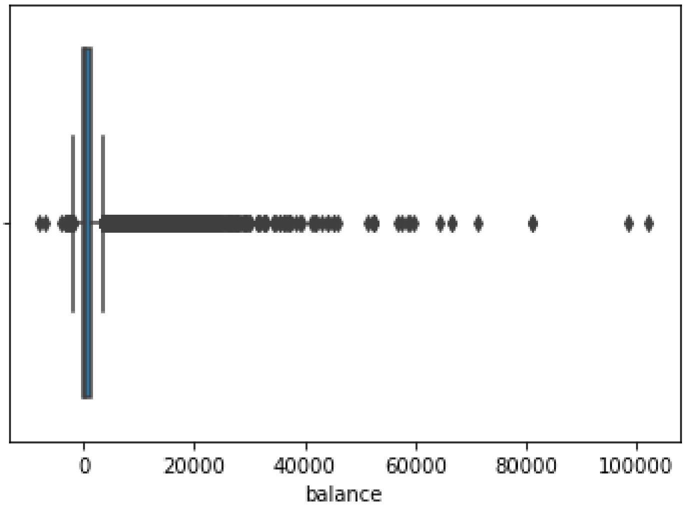
Out[34]:

```
count     45161.000000
mean       1362.850690
std        3045.939589
min       -8019.000000
25%          72.000000
50%         448.000000
75%        1428.000000
max      102127.000000
Name: balance, dtype: float64
```

In [35]:

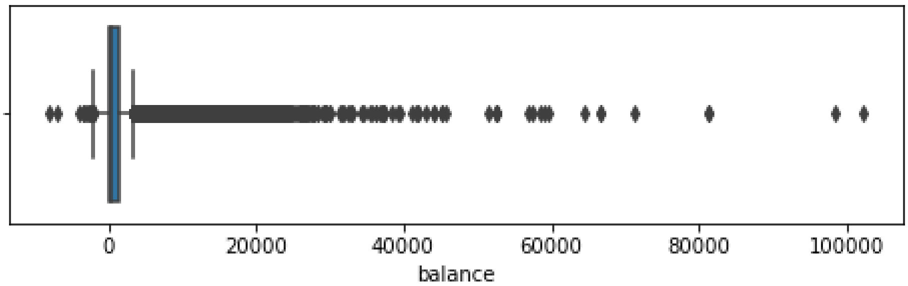
```
#plot the boxplot of balance variable.

sns.boxplot(inp1.balance)
plt.show()
```



In [36]:

```
#plot the boxplot of balance variable after scaling in 8:2.
plt.figure(figsize=[8,2])
sns.boxplot(inp1.balance)
plt.show()
```



In [37]:

```
#print the quantile (0.5, 0.7, 0.9, 0.95 and 0.99) of balance variable
inp1.balance.quantile([0.5, 0.7, 0.9, 0.95, 0.99])
```

Out[37]:

```
0.50      448.0
0.70     1126.0
0.90     3576.0
0.95     5769.0
0.99    13173.4
Name: balance, dtype: float64
```

In [38]:

```
#describe the inp1 dataset for balance variable to be greater than 15000 in inp1.
inp1[inp1.balance>15000].describe()
```

Out[38]:

	age	salary	balance	day	campaign	pdays	prev
count	351.000000	351.000000	351.000000	351.000000	351.000000	62.000000	351.00
mean	45.341880	70008.547009	24295.780627	16.022792	2.749288	188.516129	0.55
std	12.114333	34378.272805	12128.560693	8.101819	3.036886	118.796388	1.78
min	23.000000	0.000000	15030.000000	1.000000	1.000000	31.000000	0.00
25%	35.000000	50000.000000	17074.000000	9.000000	1.000000	96.250000	0.00
50%	44.000000	60000.000000	20723.000000	18.000000	2.000000	167.500000	0.00
75%	55.000000	100000.000000	26254.000000	21.000000	3.000000	246.500000	0.00
max	84.000000	120000.000000	102127.000000	31.000000	31.000000	589.000000	23.00

Segment- 6, Standardising values

Checklist for data standardization exercises:

- **Standardise units**: Ensure all observations under one variable are expressed in a common and consistent unit, e.g., convert lbs to kg, miles/hr to km/hr, etc.
- **Scale values if required**: Make sure all the observations under one variable have a common scale.
- **Standardise precision** for better presentation of data, e.g., change 4.5312341 kg to 4.53 kg.
- **Remove extra characters** such as common prefixes/suffixes, leading/trailing/multiple spaces, etc. These are irrelevant to analysis.
- **Standardise case**: String variables may take various casing styles, e.g., UPPERCASE, lowercase, Title Case, Sentence case, etc.
- **Standardise format**: It is important to standardise the format of other elements such as date, name, etce.g., change 23/10/16 to 2016/10/23, “Modi, Narendra” to “Narendra Modi", etc.

Duration variable

In [39]:

```
inp1.duration.head(10)
```

Out[39]:

```
0    261 sec
1    151 sec
2     76 sec
3     92 sec
4    198 sec
5    139 sec
6    217 sec
7    380 sec
8     50 sec
9     55 sec
Name: duration, dtype: object
```

In [40]:

```
#describe the duration variable of inp1
inp1.duration.describe()
```

Out[40]:

```
count       45161
unique       2646
top       1.5 min
freq          138
Name: duration, dtype: object
```

In [41]:

```
#convert the duration variable into single unit i.e. minutes. and remove the sec or r
inp1.duration=inp1.duration.apply(lambda x: float(x.split()[0])/60 if x.find("sec")>
```

In [42]:

```
#describe the duration variable
inp1.duration.describe()
```

Out[42]:

```
count    45161.000000
mean         4.302774
std          4.293129
min          0.000000
25%          1.716667
50%          3.000000
75%          5.316667
max         81.966667
Name: duration, dtype: float64
```

Session- 3, Univariate Analysis

Segment- 2, Categorical unordered univariate analysis

Unordered data do not have the notion of high-low, more-less etc. Example:

- Type of loan taken by a person = home, personal, auto etc.
- Organisation of a person = Sales, marketing, HR etc.
- Job category of persone.
- Marital status of any one.

Marital status

In [43]:

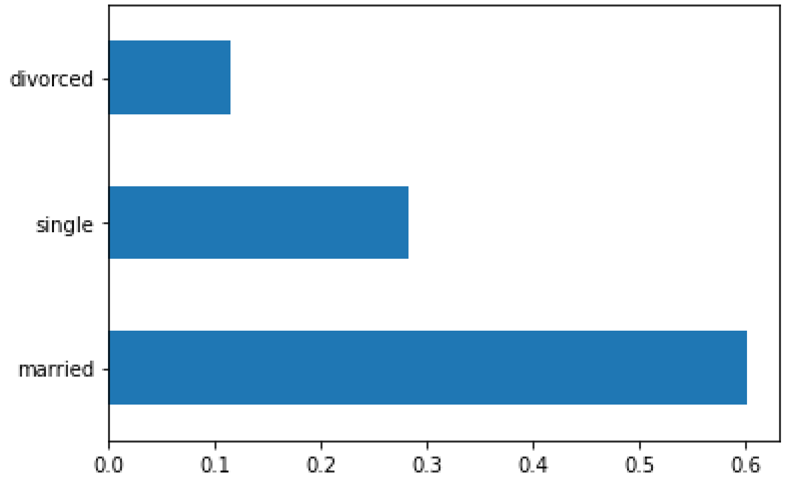
```
#calculate the percentage of each marital status category.
inp1.marital.value_counts(normalize= True)
```

Out[43]:

```
married     0.601957
single      0.282943
divorced    0.115099
Name: marital, dtype: float64
```

In [44]:

```
#plot the bar graph of percentage marital status categories
inp1.marital.value_counts(normalize= True).plot.barh()
plt.show()
```



Job

In [45]:

```
#calculate the percentage of each job status category.
inp1.job.value_counts(normalize= True)
```

Out[45]:

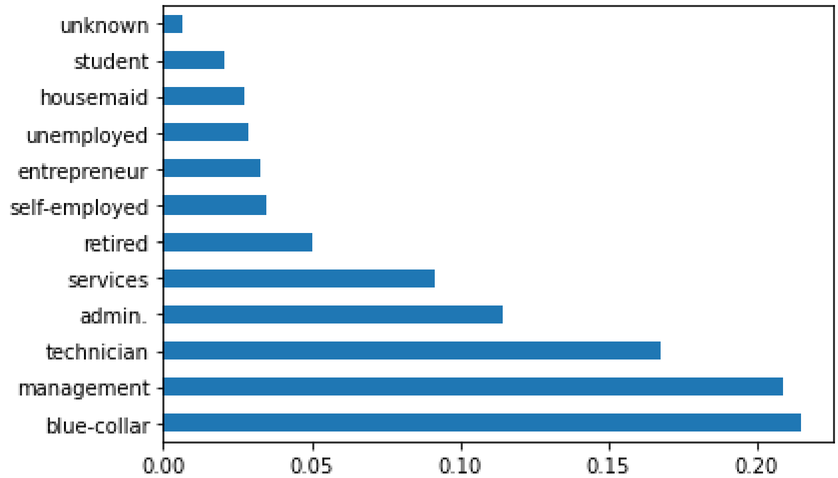
```
blue-collar      0.215274
management       0.209273
technician       0.168043
admin.           0.114369
services         0.091849
retired          0.050087
self-employed    0.034853
entrepreneur     0.032860
unemployed       0.028830
housemaid        0.027413
student          0.020770
unknown          0.006377
Name: job, dtype: float64
```

In [46]:

```
#plot the bar graph of percentage job categories
inp1.job.value_counts(normalize= True).plot.barh()
plt.plot()
```

Out[46]:

```
[]
```



Segment- 3, Categorical ordered univariate analysis

Ordered variables have some kind of ordering. Some examples of bank marketing dataset are:

- Age group= <30, 30-40, 40-50 and so on.
- Month = Jan-Feb-Mar etc.
- Education = primary, secondary and so on.

Education

In [47]:

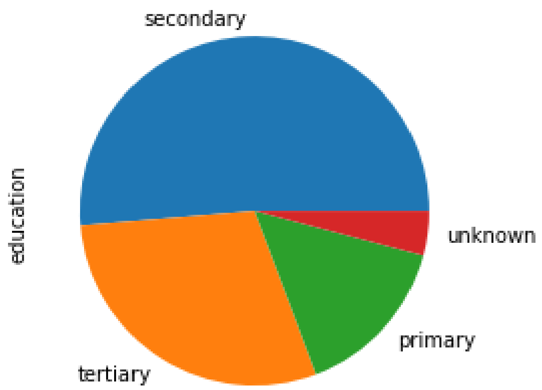
```
#calculate the percentage of each education category.
inp1.education.value_counts(normalize= True)
```

Out[47]:

```
secondary    0.513275
tertiary     0.294192
primary      0.151436
unknown      0.041097
Name: education, dtype: float64
```

In [48]:

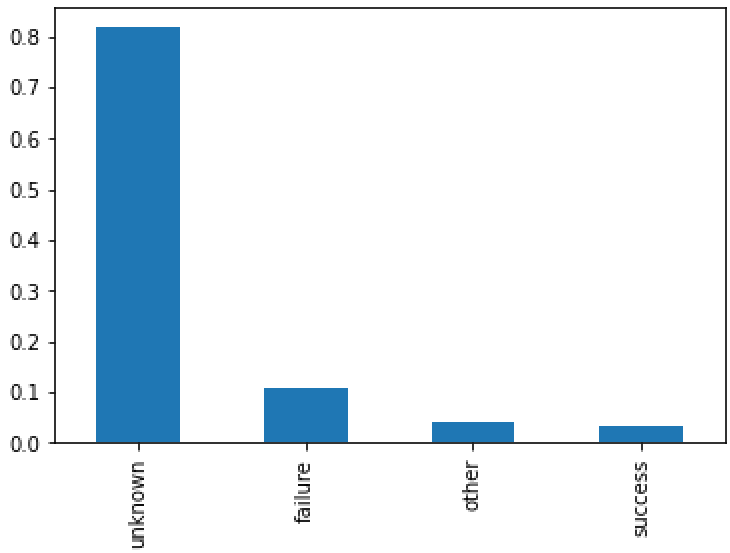
```
#plot the pie chart of education categories
inp1.education.value_counts(normalize= True).plot.pie()
plt.show()
```



poutcome

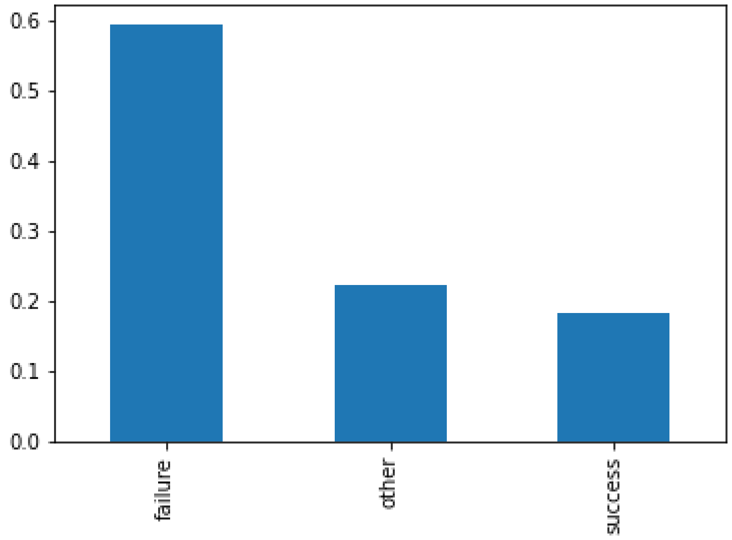
In [49]:

```
#calculate the percentage of each poutcome category.
inp1.poutcome.value_counts(normalize= True).plot.bar()
plt.show()
```



In [50]:

```
inp1[-(inp1.poutcome=="unknown")].poutcome.value_counts(normalize= True).plot.bar()
plt.show()
```



Response the target variable

In [53]:

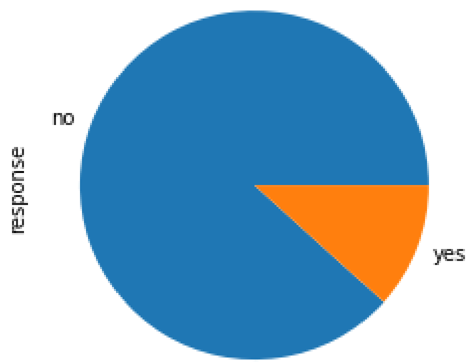
```
#calculate the percentage of each response category.
inp1.response.value_counts(normalize= True)
```

Out[53]:

```
no     0.882974
yes    0.117026
Name: response, dtype: float64
```

In [54]:

```
#plot the pie chart of response categories
inp1.response.value_counts(normalize= True).plot.pie()
plt.show()
```



Session- 4, Bivariate and Multivariate Analysis

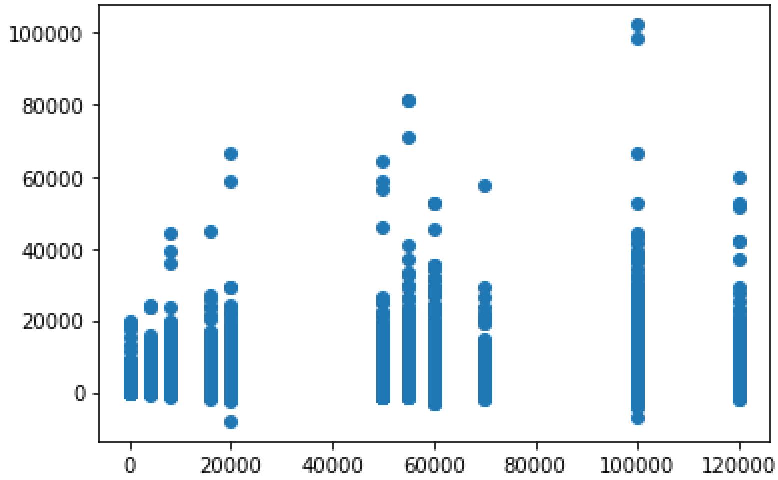
Segment-2, Numeric- numeric analysis

There are three ways to analyse the numeric- numeric data types simultaneously.

- **Scatter plot**: describes the pattern that how one variable is varying with other variable.
- **Correlation matrix**: to describe the linearity of two numeric variables.
- **Pair plot**: group of scatter plots of all numeric variables in the data frame.

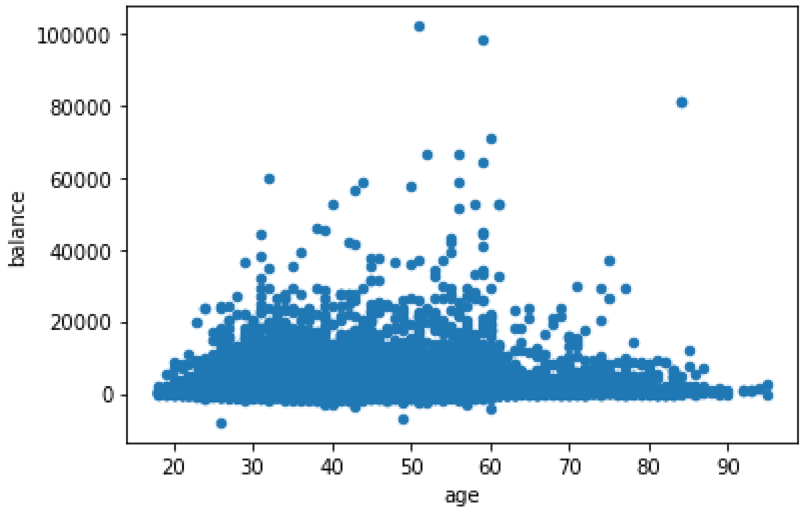
In [55]:

```
#plot the scatter plot of balance and salary variable in inp1
plt.scatter(inp1.salary, inp1.balance)
plt.show()
```



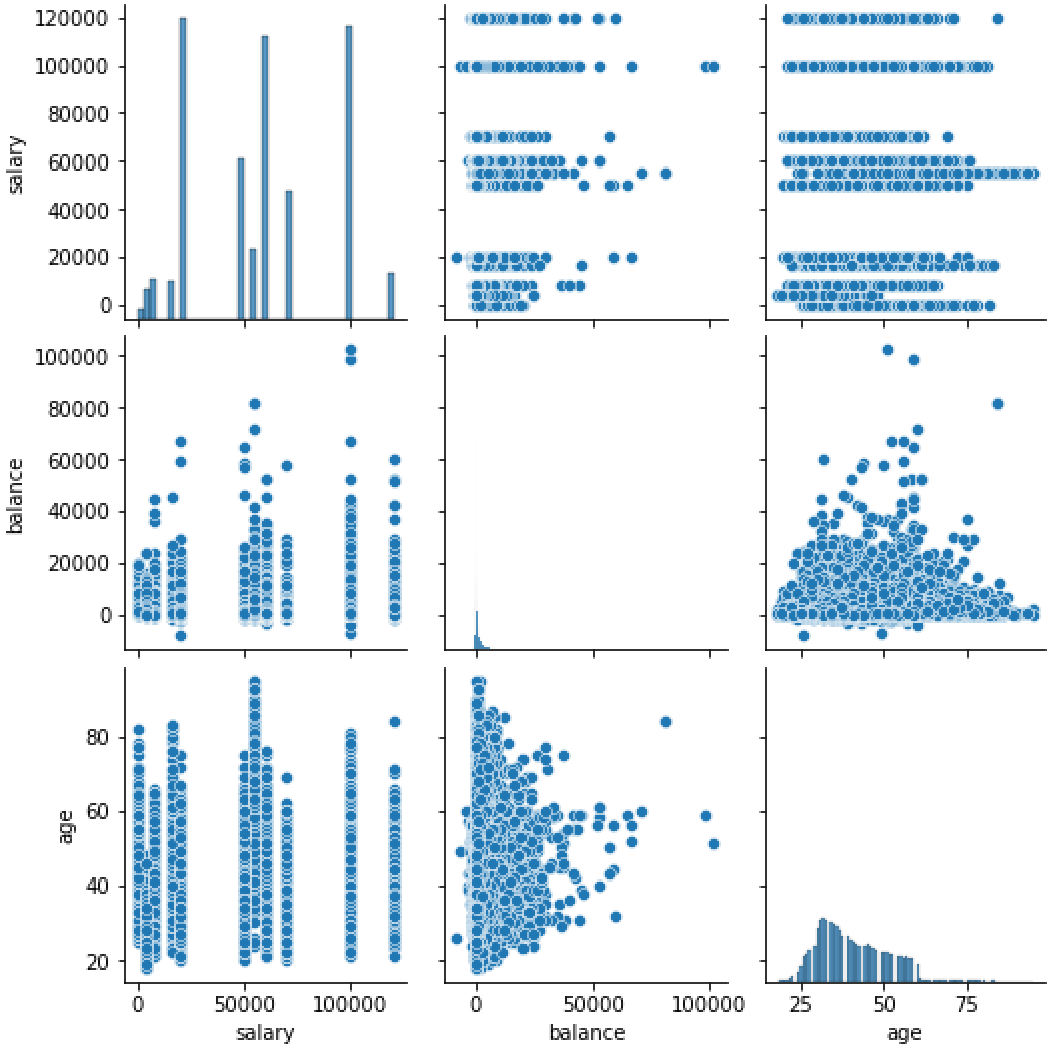
In [56]:

```
#plot the scatter plot of balance and age variable in inp1
inp1.plot.scatter(x='age', y='balance')
plt.show()
```



In [57]:

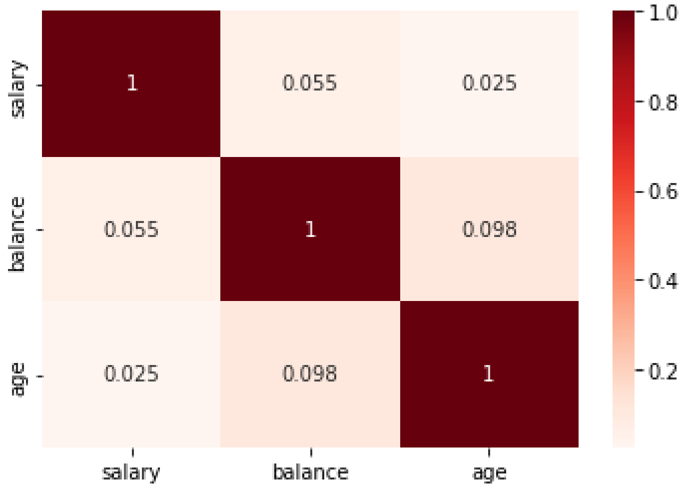
```
#plot the pair plot of salary, balance and age in inp1 dataframe.
sns.pairplot(data=inp1, vars=["salary","balance", "age"])
plt.show()
```



Correlation heat map

In [58]:

```
#plot the correlation matrix of salary, balance and age in inp1 dataframe.
sns.heatmap( inp1[["salary","balance", "age"]].corr(), annot= True, cmap= "Reds")
plt.show()
```



Segment- 4, Numerical categorical variable

Salary vs response

In [59]:

```
#groupby the response to find the mean of the salary with response no & yes seperatl
inp1.groupby("response")["salary"].mean()
```

Out[59]:

```
response
no     56769.510482
yes    58780.510880
Name: salary, dtype: float64
```

In [60]:

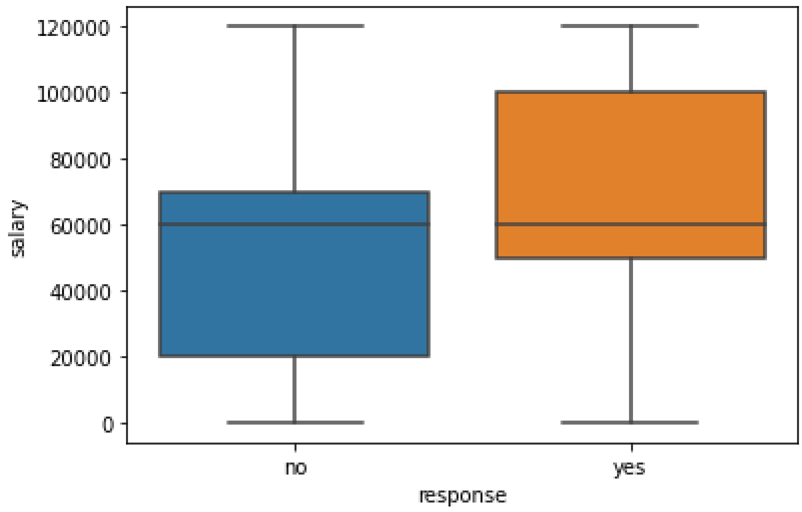
```
#groupby the response to find the median of the salary with response no & yes sepera
inp1.groupby("response")["salary"].median()
```

Out[60]:

```
response
no     60000.0
yes    60000.0
Name: salary, dtype: float64
```

In [61]:

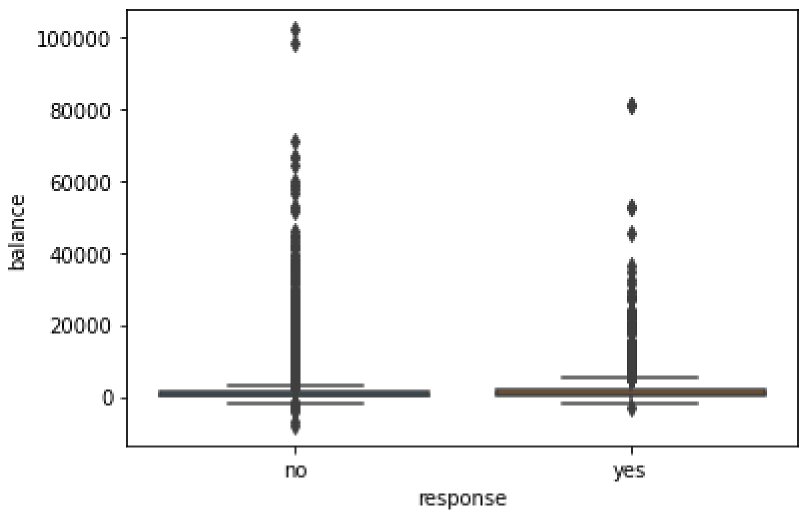
```
#plot the box plot of salary for yes & no responses.
sns.boxplot(data=inp1,x="response", y="salary")
plt.show()
```



Balance vs response

In [63]:

```
#plot the box plot of balance for yes & no responses.
sns.boxplot(data=inp1,x="response", y="balance")
plt.show()
```



In [64]:

```
#groupby the response to find the mean of the balance with response no & yes seperat
inp1.groupby("response")["balance"].mean()
```

Out[64]:

```
response
no     1304.292281
yes    1804.681362
Name: balance, dtype: float64
```

In [65]:

```
#groupby the response to find the median of the balance with response no & yes seper
inp1.groupby("response")["balance"].median()
```

Out[65]:

```
response
no      417.0
yes     733.0
Name: balance, dtype: float64
```

75th percentile

In [66]:

```
#function to find the 75th percentile.
def p75(x):
    return np.quantile(x, 0.75)
```

In [67]:

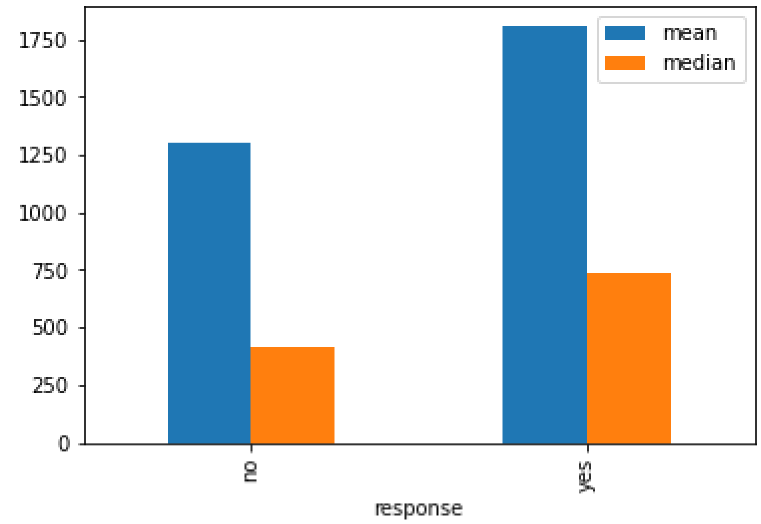
```
#calculate the mean, median and 75th percentile of balance with response
inp1.groupby("response")["balance"].aggregate(["mean","median",p75])
```

Out[67]:

response	mean	median	p75
no	1304.292281	417.0	1345.0
yes	1804.681362	733.0	2159.0

In [68]:

```
#plot the bar graph of balance's mean an median with response.
inp1.groupby("response")["balance"].aggregate(["mean","median"]).plot.bar()
plt.show()
```



Education vs salary

In [69]:

```
#groupby the education to find the mean of the salary education category.
inp1.groupby("education")["salary"].mean()
```

Out[69]:

```
education
primary      34232.343910
secondary    49731.449525
tertiary     82880.249887
unknown      46529.633621
Name: salary, dtype: float64
```

In [70]:

```
#groupby the education to find the median of the salary for each education category.
inp1.groupby("education")["salary"].median()
```

Out[70]:

```
education
primary       20000.0
secondary     55000.0
tertiary     100000.0
unknown       50000.0
Name: salary, dtype: float64
```

Job vs salary

In [71]:

```
#groupby the job to find the mean of the salary for each job category.
inp1.groupby('job')['salary'].mean()
```

Out[71]:

```
job
admin.            50000.0
blue-collar       20000.0
entrepreneur     120000.0
housemaid         16000.0
management       100000.0
retired           55000.0
self-employed     60000.0
services          70000.0
student            4000.0
technician        60000.0
unemployed         8000.0
unknown               0.0
Name: salary, dtype: float64
```

In [72]:

```
inp1.groupby('job')['salary'].median()
```

Out[72]:

```
job
admin.            50000.0
blue-collar       20000.0
entrepreneur     120000.0
housemaid         16000.0
management       100000.0
retired           55000.0
self-employed     60000.0
services          70000.0
student            4000.0
technician        60000.0
unemployed         8000.0
unknown               0.0
Name: salary, dtype: float64
```

Segment- 5, Categorical categorical variable

In [73]:

```
#create response_flag of numerical data type where response "yes"= 1, "no"= 0
inp1["response_flag"]=np.where(inp1.response=="yes", 1, 0)
inp1.response.value_counts()
```

Out[73]:

```
no     39876
yes     5285
Name: response, dtype: int64
```

In [74]:

```
inp1.response.value_counts(normalize= True)
```

Out[74]:

```
no     0.882974
yes    0.117026
Name: response, dtype: float64
```

In [75]:

```
inp1.response_flag.mean()
```

Out[75]:

```
0.1170257523084077
```

Education vs response rate

In [76]:

```
#calculate the mean of response_flag with different education categories.
inp1.groupby("education")["response_flag"].mean()
```

Out[76]:

```
education
primary      0.086416
secondary    0.105608
tertiary     0.150083
unknown      0.135776
Name: response_flag, dtype: float64
```

Marital vs response rate

In [77]:

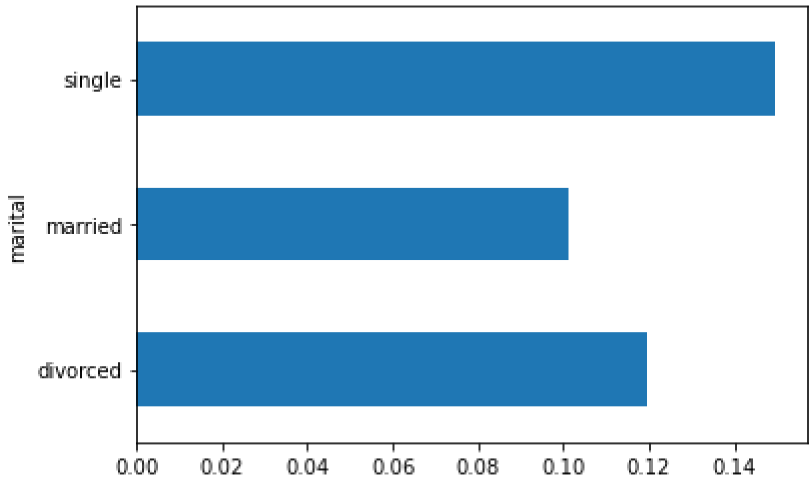
```
#calculate the mean of response_flag with different marital status categories.
inp1.groupby(["marital"])["response_flag"].mean()
```

Out[77]:

```
marital
divorced    0.119469
married     0.101269
single      0.149554
Name: response_flag, dtype: float64
```

In [78]:

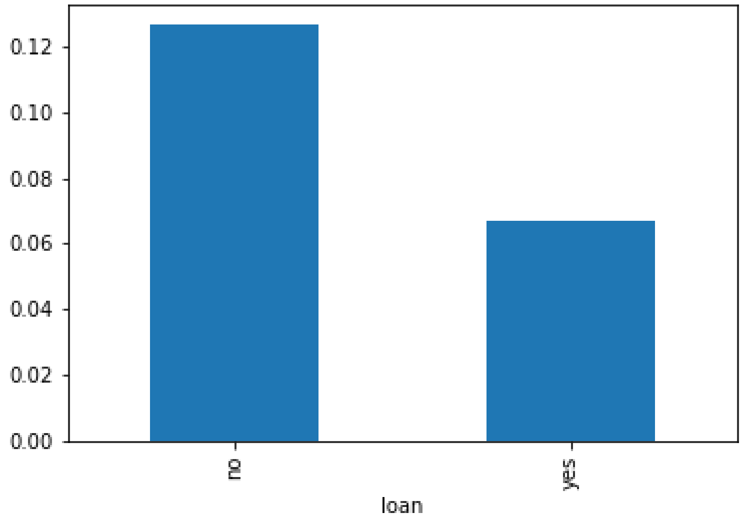
```
#plot the bar graph of marital status with average value of response_flag
inp1.groupby(["marital"])["response_flag"].mean().plot.barh()
plt.show()
```



Loans vs response rate

In [80]:

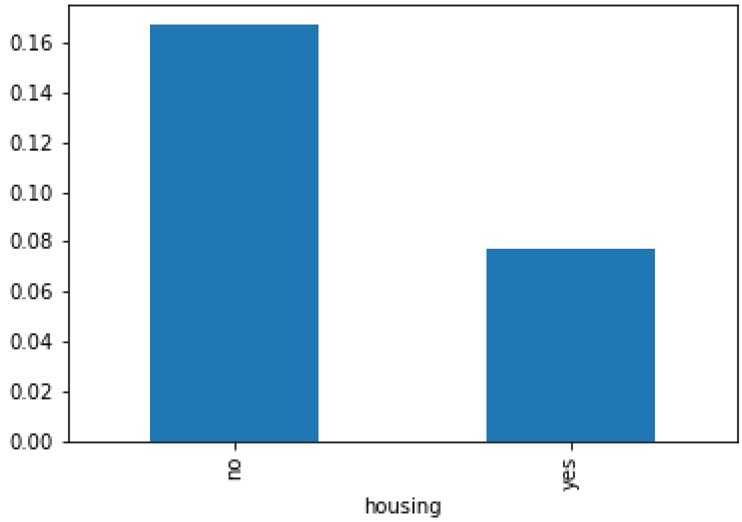
```
#plot the bar graph of personal loan status with average value of response_flag
inp1.groupby(["loan"])["response_flag"].mean().plot.bar()
plt.show()
```



Housing loans vs response rate

In [81]:

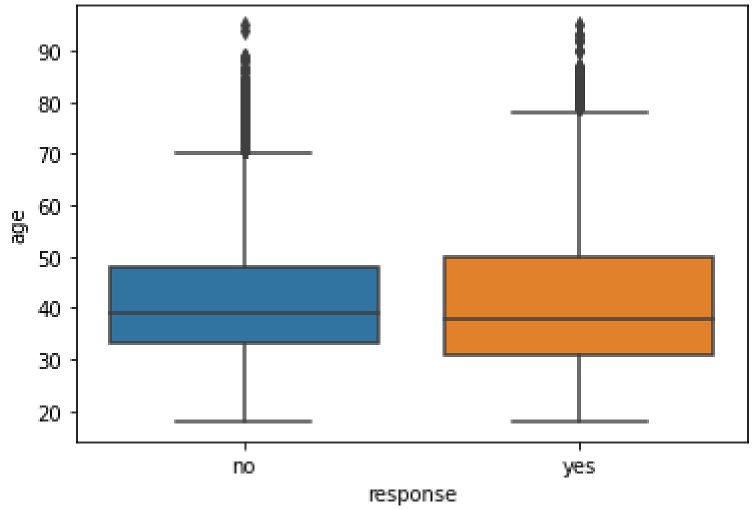
```
#plot the bar graph of housing loan status with average value of response_flag
inp1.groupby(["housing"])["response_flag"].mean().plot.bar()
plt.show()
```



Age vs response

In [82]:

```
#plot the boxplot of age with response_flag
sns.boxplot(data=inp1, x="response",y="age")
plt.show()
```



making buckets from age columns

In [84]:

```
#create the buckets of <30, 30-40, 40-50 50-60 and 60+ from age column.
pd.cut(inp1.age[:5],[0, 30, 40, 50, 60, 9999], labels= ["<30","30-40","40-50","50-60
```

Out[84]:

```
0    50-60
1    40-50
2    30-40
3    40-50
4    30-40
Name: age, dtype: category
Categories (5, object): ['<30' < '30-40' < '40-50' < '50-60' < '60+']
```

In [85]:

```
inp1.age.head()
```

Out[85]:

```
0    58.0
1    44.0
2    33.0
3    47.0
4    33.0
Name: age, dtype: float64
```

In [86]:

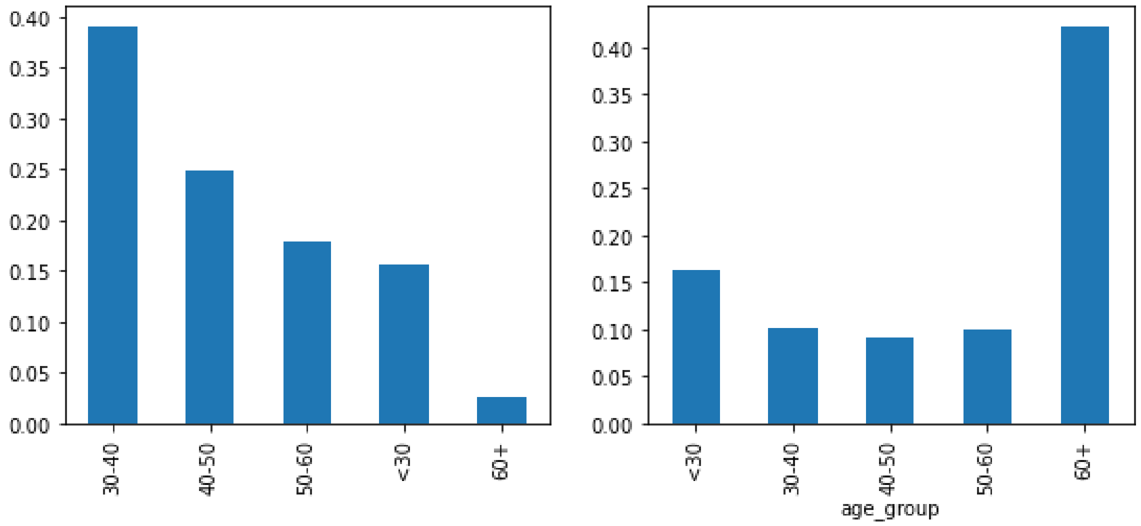
```
inp1["age_group"]=pd.cut(inp1.age,[0, 30, 40, 50, 60, 9999], labels= ["<30","30-40",
inp1.age_group.value_counts(normalize= True)
```

Out[86]:

```
30-40    0.391090
40-50    0.248688
50-60    0.178406
<30      0.155555
60+      0.026262
Name: age_group, dtype: float64
```

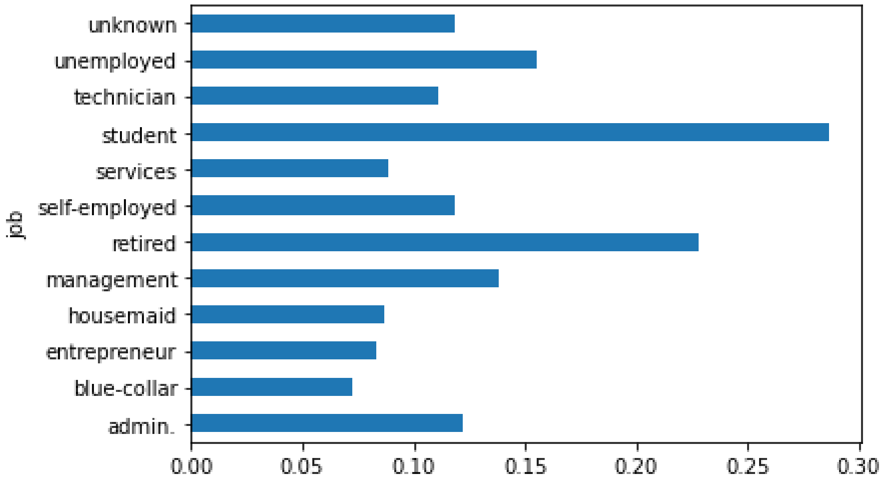
In [87]:

```
#plot the percentage of each buckets and average values of response_flag in each buck
plt.figure(figsize=[10,4])
plt.subplot(1, 2, 1)
inp1.age_group.value_counts(normalize= True).plot.bar()
plt.subplot(1, 2, 2)
inp1.groupby(['age_group'])['response_flag'].mean().plot.bar()
plt.show()
```



In [88]:

```
#plot the bar graph of job categories with response_flag mean value.
inp1.groupby(['job'])['response_flag'].mean().plot.barh()
plt.show()
```



Segment-6, Multivariate analysis

Education vs marital vs response

In [90]:

```
res=pd.pivot_table(data=inp1, index="education", columns="marital", values="response_
res
```

Out[90]:

marital	divorced	married	single
education			
primary	0.138852	0.075601	0.106808
secondary	0.103559	0.094650	0.129271
tertiary	0.137415	0.129835	0.183737
unknown	0.142012	0.122519	0.162879

In [91]:

```
#create heat map of education vs marital vs response_flag
sns.heatmap(res, annot= True, cmap="RdYlGn")
plt.show()
```

In [92]:

```
sns.heatmap(res, annot= True, cmap="RdYlGn", center= 0.117)
plt.show()
```

Job vs marital vs response

In [93]:

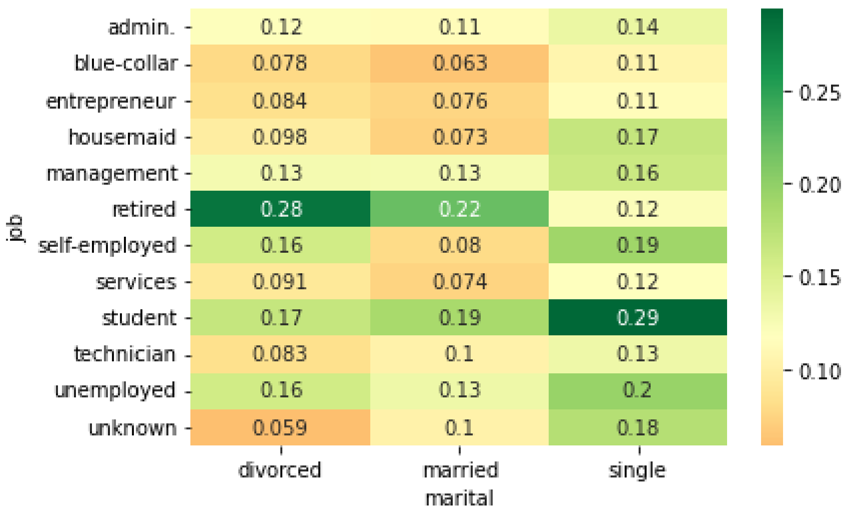
```
res=pd.pivot_table(data=inp1, index="job", columns="marital", values="response_flag"
res
```

Out[93]:

marital	divorced	married	single
job			
admin.	0.120160	0.113383	0.136153
blue-collar	0.077644	0.062778	0.105760
entrepreneur	0.083799	0.075843	0.113924
housemaid	0.097826	0.072527	0.166667
management	0.127928	0.126228	0.162254
...	...	...	...
services	0.091241	0.074105	0.117696
student	0.166667	0.185185	0.293850
technician	0.083243	0.102767	0.132645
unemployed	0.157895	0.132695	0.195000
unknown	0.058824	0.103448	0.176471

In [94]:

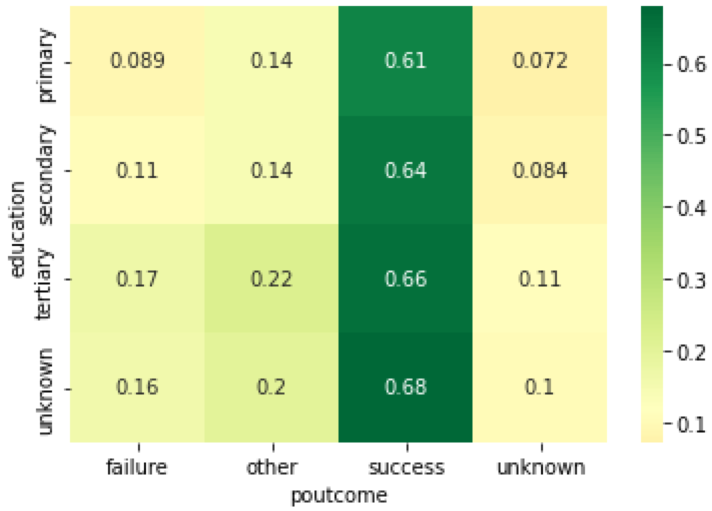
```
#create the heat map of Job vs marital vs response_flag.
sns.heatmap(res, annot= True, cmap="RdYlGn", center= 0.117)
plt.show()
```



Education vs poutcome vs response

In [95]:

```
#create the heat map of education vs poutcome vs response_flag.
res=pd.pivot_table(data=inp1, index="education", columns="poutcome", values="respons
sns.heatmap(res, annot= True, cmap="RdYlGn", center= 0.117)
plt.show()
```



In [96]:

```
inp1[inp1.pdays>0].response_flag.mean()
```

Out[96]:

0.2307785593014795

In [98]:

```
res=pd.pivot_table(data=inp1, index="education", columns="poutcome", values="respons
sns.heatmap(res, annot= True, cmap="RdYlGn", center= 0.2308)
plt.show()
```