In [1]:
```
print('EDA for a Bank Marketing Campaign and deciding factors - Anurag Agarwal')
```
```
EDA for a Bank Marketing Campaign and deciding factors - Anurag Agarwal
```

> ## EDA for a Bank Marketing Campaign and deciding factors

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from math import *
import seaborn as sns
import scipy.stats as stats
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

import plotly.express as px
import plotly, io as style
```

In [3]:
```
a= pd.read_excel('Attribute details.xlsx')
a.head(3)
```

Out[3]:

	Attributes details	Unnamed: 1
0	Customer id	This column is about the id of the customer co...
1	age	This column consists of the age of each customer
2	salary	This column represents monthly salary of the c...

In [4]:
```
## Section based on the file

bm= pd.read_csv('bankupdated.csv')

bm.head(3)
```

Out[4]:

	banking marketing	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unname
0	customer id and age.	NaN	Customer salary and balance.	NaN	Customer marital status and job with education...	NaN	particular customer before targeted or not	NaN	Loan types: loans or housing loans	Na
1	customerid	age	salary	balance	marital	jobedu	targeted	default	housing	loa
2	1	58	100000	2143	married	management,tertiary	yes	no	yes	n

In [5]:
```
## skip row will remove unnecessery headers or rows

bm= pd.read_csv('bankupdated.csv', skiprows=2)
bm.head(3)
```

Out[5]:

	customerid	age	salary	balance	marital	jobedu	targeted	default	housing	loan	contact	day	mont
0	1	58.0	100000	2143	married	management,tertiary	yes	no	yes	no	unknown	5	ma 201
1	2	44.0	60000	29	single	technician,secondary	yes	no	yes	no	unknown	5	ma 201
2	3	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	unknown	5	ma 201

In [6]:
```
bm.dtypes
```

Out[6]:
```
customerid      int64
age           float64
salary          int64
balance         int64
marital        object
jobedu         object
targeted       object
default        object
housing        object
loan           object
contact        object
day             int64
month          object
duration       object
campaign        int64
pdays           int64
previous        int64
poutcome       object
response       object
dtype: object
```

In [7]:
```python
## average age of customers

bm.age.mean()
```

Out[7]:
```
40.93565090394105
```

In [8]:
```python
bm.shape
```

Out[8]:
```
(45211, 19)
```

In [ ]:
```python
## Cleaning data
```

In [9]:
```python
# 1. delet cust id

bm.drop("customerid", axis=1, inplace= True)
```

In [10]:
```python
# 2. Split jobedu to job and education

bm['job']= bm.jobedu.apply(lambda x: x.split(",")[0])

bm['edu']= bm.jobedu.apply(lambda x: x.split(",")[1])
```

In [11]:
```python
# 3. now drop jobedu col as we alraedy created job and edu col

bm.drop("jobedu", axis=1, inplace= True)
```

In [12]:
```python
## recheck data

bm.head(2)
```

Out[12]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017	261 sec	1	-1	
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017	151 sec	1	-1	

In [13]:
```python
## data cleaning for missing or null values

bm.isnull().sum()
```

Out[13]:
```
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
edu           0
dtype: int64
```

In [ ]:
```
## age have missing 20 which will convert in to int
## month have 50 missing values so first we need to handle that
## resonce have 30 missing value

## we need to clear all this data
```

In [14]:
```
## first will clean age col

float(100.0*20/452111) ## as value is less then 0.001 percent will delet the data
```

Out[14]:
```
0.004423692411819221
```

In [15]:
```
## as value is less then 0.001 percent will delet the data

bm1= bm[~bm.age.isnull()].copy()

bm1.age.isnull().sum()
```

Out[15]:
```
0
```

In [16]:
```
## will clean month col.

float(100.0*50/452111)
```

Out[16]:
```
0.011059231029548054
```

In [17]:
```
## avg of month null val is 0.01. we can drop this data too. but will use new starategy to replace it with

bm.month.value_counts()
```

Out[17]:
```
may, 2017    13747
jul, 2017     6888
aug, 2017     6240
jun, 2017     5335
nov, 2017     3968
apr, 2017     2931
feb, 2017     2646
jan, 2017     1402
oct, 2017      738
sep, 2017      576
mar, 2017      476
dec, 2017      214
Name: month, dtype: int64
```

In [18]:
```
bm1.month.fillna(bm1.month.value_counts()[0], inplace=True)

bm1.head()
```

Out[18]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017	261 sec	1	-1	
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017	151 sec	1	-1	
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may, 2017	76 sec	1	-1	
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may, 2017	92 sec	1	-1	
4	33.0	0	1	single	no	no	no	no	unknown	5	may, 2017	198 sec	1	-1	

In [19]:

```
bm1.month.isnull().sum()
```

Out[19]:

```
0
```

In [20]:

```
bm1.month.value_counts(normalize= True)
```

Out[20]:

```
may, 2017    0.304043
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
13740        0.001106
Name: month, dtype: float64
```

In [21]:

```
## spliting month

bm1['month']= bm1["month"].apply(lambda x : str(x).split(",")[0])
bm1.head()
```

Out[21]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may	261 sec	1	-1	
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may	151 sec	1	-1	
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may	76 sec	1	-1	
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may	92 sec	1	-1	
4	33.0	0	1	single	no	no	no	no	unknown	5	may	198 sec	1	-1	

In [22]:

```
## pdays and response col

bm1.isnull().sum()
```

Out[22]:
```
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    30
job          0
edu          0
dtype: int64
```

In [23]:
```
## pdays missing values which is showing -1

bm1.pdays.value_counts()
```

Out[23]:
```
-1      36939
 182      167
 92       146
 91       126
 183      126
         ...
 449        1
 452        1
 648        1
 595        1
 530        1
Name: pdays, Length: 558, dtype: int64
```

In [24]:
```
## -1 is in data is having count of 36939 hence we can not drop it

bm1.pdays.describe()
```

Out[24]:
```
count    45191.000000
mean        40.181253
std        100.074099
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

In [25]:
```
## replace -1 with NaN, as statical calculations will automaticly ignore it

bm1.loc[bm1.pdays<0,"pdays"]= np.NaN
```

In [26]:
```
## replaced -1, and now calculations ignored NaN

bm1.pdays.describe()
```

Out[26]:
```
count    8252.000000
mean      224.523752
std       115.202715
min         1.000000
25%       133.000000
50%       194.500000
75%       327.000000
max       871.000000
Name: pdays, dtype: float64
```

In [27]:
```
## cleaning and droping responce col as

float(100.0*30/452111)
```

Out[27]: 0.006635538617728832

In [28]:
```
## as value is less then 0.001 percent will delet the data

bm2= bm1[~bm1.response.isnull()].copy()

bm2.response.isnull().sum()
```

Out[28]: 0

In [29]:
```
bm2.shape
```

Out[29]: (45161, 19)

In [30]:
```
bm2.isnull().sum()
```

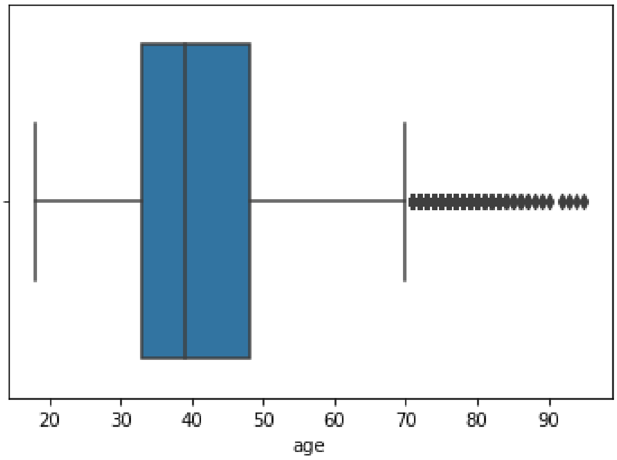
Out[30]:
```
age             0
salary          0
balance         0
marital         0
targeted        0
default         0
housing         0
loan            0
contact         0
day             0
month           0
duration        0
campaign        0
pdays       36915
previous        0
poutcome        0
response        0
job             0
edu             0
dtype: int64
```

In [ ]:
```
## Handaling outliers for numerical values cols which are- age, salary, balance,
```

In [31]:
```
# for age

bm1.age.describe()
```

Out[31]:
```
count    45191.000000
mean        40.935651
std         10.619198
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64
```

In [32]:
```
## as we see not much difference bw data point hence no outliers, will verify with boxplot

sns.boxplot(bm1.age)
plt.show()
```

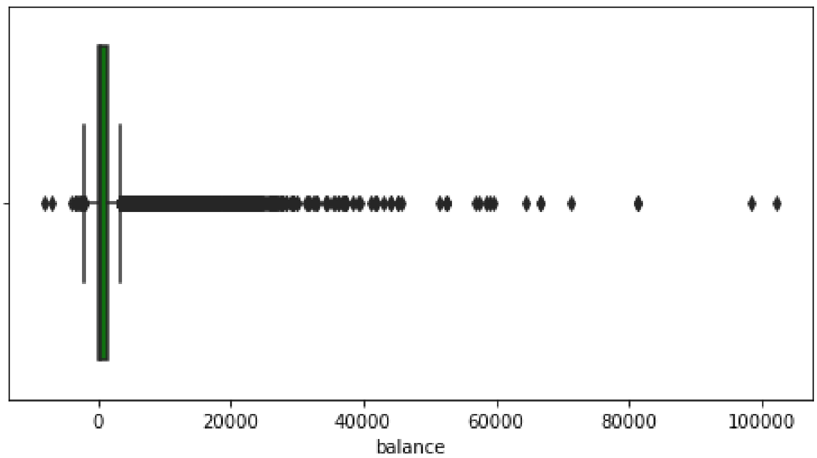


In [33]:
```
### for Balance

bm1.balance.describe()
```

Out[33]:
```
count     45191.000000
mean       1362.432520
std        3045.120417
min       -8019.000000
25%          72.000000
50%         448.000000
75%        1428.000000
max      102127.000000
Name: balance, dtype: float64
```

In [34]:
```
## as we say huge diff bw percentile will use more methods to check if outliers are valid or essential

plt.figure(figsize=[8,4])
sns.boxplot(bm1.balance, color='green')
```

Out[34]:
```
<AxesSubplot:xlabel='balance'>
```



In [35]:
```
### as we can see still some data is in outlier range we check it further by looking the quantlies

bm1.balance.quantile([0.5,0.7,0.9,0.95,0.99])
```

Out[35]:
```
0.50      448.0
0.70     1126.0
0.90     3575.0
0.95     5768.0
0.99    13167.1
Name: balance, dtype: float64
```

In [36]:
```
## we need to see the data which is higher the 0.99 percentile/quantile to check if its genuine and essent

bm1[bm1.balance>15000].describe()
```

Out[36]:

	age	salary	balance	day	campaign	pdays	previous
count	351.000000	351.000000	351.000000	351.000000	351.000000	62.000000	351.000000
mean	45.341880	70008.547009	24295.780627	16.022792	2.749288	188.516129	0.555556
std	12.114333	34378.272805	12128.560693	8.101819	3.036886	118.796388	1.784590
min	23.000000	0.000000	15030.000000	1.000000	1.000000	31.000000	0.000000
25%	35.000000	50000.000000	17074.000000	9.000000	1.000000	96.250000	0.000000
50%	44.000000	60000.000000	20723.000000	18.000000	2.000000	167.500000	0.000000
75%	55.000000	100000.000000	26254.000000	21.000000	3.000000	246.500000	0.000000
max	84.000000	120000.000000	102127.000000	31.000000	31.000000	589.000000	23.000000

In [37]:

```
## its all valid and important data as these people shows positive interestin campaign

bm1[bm1.balance>15000].head()
```

Out[37]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays
334	45.0	100000	24598	divorced	no	no	yes	no	unknown	5	may	313 sec	3	NaN
446	39.0	60000	45248	single	no	no	yes	no	unknown	6	may	1623 sec	1	NaN
920	44.0	50000	58544	married	yes	no	yes	no	unknown	7	may	144 sec	2	NaN
2065	55.0	55000	18722	married	yes	no	yes	no	unknown	12	may	128 sec	2	NaN
2343	26.0	60000	24299	single	yes	no	yes	no	unknown	13	may	704 sec	1	NaN

In [38]:

```
## For salary

bm1.salary.describe()
```

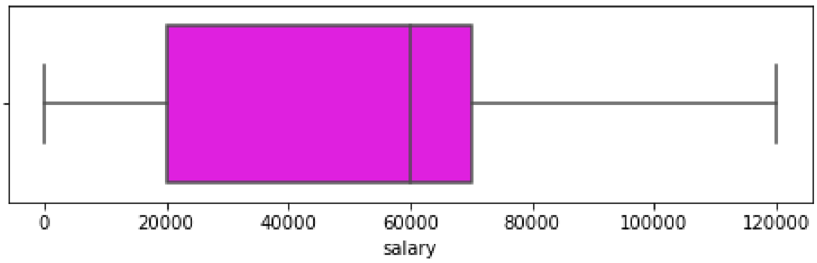
Out[38]:

```
count      45191.000000
mean       57005.974641
std        32084.253154
min            0.000000
25%        20000.000000
50%        60000.000000
75%        70000.000000
max       120000.000000
Name: salary, dtype: float64
```

In [39]:

```
##to check outliers in salary

plt.figure(figsize=[8,2])
sns.boxplot(bm1.salary, color='magenta')
```

Out[39]: <AxesSubplot:xlabel='salary'>



In [40]:

```
##to check outliers in salary as we can see no difference bw 0.99 to max

bm1.salary.quantile([0.5,0.7,0.9,0.95,0.99])
```

Out[40]:
```
0.50     60000.0
0.70     70000.0
0.90    100000.0
0.95    100000.0
0.99    120000.0
Name: salary, dtype: float64
```

In [41]:
```
### Standardization of Data

print('### Standardization of Data')
```

```
### Standardization of Data
```

In [ ]:
```
3#Checklist for data standardization exercises:

# standardise units: Ensure all observations under one variable are expressed in a common and consistent u
# 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 c
# Standardise case: String variables may take various casing styles, e.g., UPPERCASE, lowercase, Title Cas
# Standardise format: It is important to standardise the format of other elements such as date, name, etce
```

In [42]:
```
bm1.duration.head()
```

Out[42]:
```
0    261 sec
1    151 sec
2     76 sec
3     92 sec
4    198 sec
Name: duration, dtype: object
```

In [43]:
```
bm1.duration.describe()
```

Out[43]:
```
count       45191
unique       2646
top       1.5 min
freq          138
Name: duration, dtype: object
```

In [44]:
```
## As some values are in sec and some are in mins will convert the whole duration format in mins

bm1.duration = bm1.duration.apply(lambda x: float(x.split()[0])/60 if x.find("sec")>0 else float(x.split(
```

In [45]:
```
bm1.duration.describe()
```

Out[45]:
```
count    45191.000000
mean         4.303030
std          4.292739
min          0.000000
25%          1.716667
50%          3.000000
75%          5.316667
max         81.966667
Name: duration, dtype: float64
```

In [46]:
```
## re- check

bm1.duration.head()
```

Out[46]:
```
0    4.350000
1    2.516667
2    1.266667
3    1.533333
4    3.300000
Name: duration, dtype: float64
```

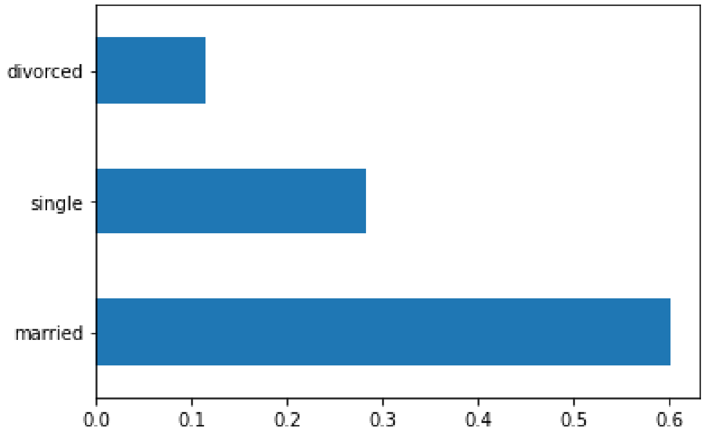
In [47]:
```
print(' EDA- 2-a Univariate Analysis')
print(' EDA- 2-a Univariate Analysis')
print(' EDA- 2-a Univariate Analysis')
print(' EDA- 2-a Univariate Analysis')
print(' EDA- 2-a Univariate Analysis')
```

```
EDA- 2-a Univariate Analysis
EDA- 2-a Univariate Analysis
EDA- 2-a Univariate Analysis
EDA- 2-a Univariate Analysis
EDA- 2-a Univariate Analysis
```

In [48]:
```
### Categorical Unordered Univariate Analysis

# marital and jobs are under categorical unorderd

bm1.marital.value_counts()
```

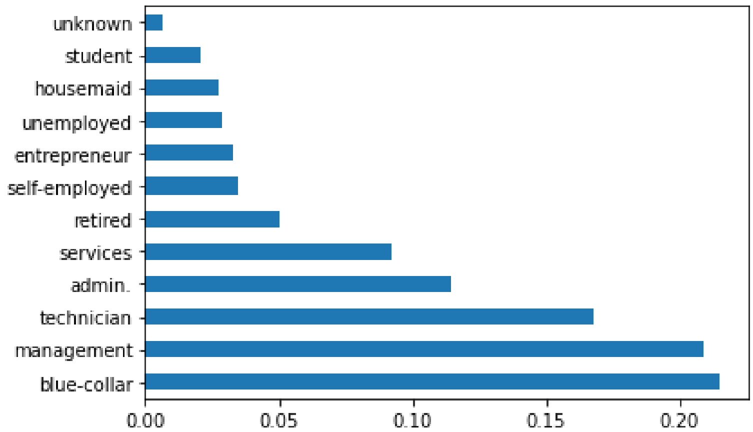
Out[48]:
```
married     27204
single      12786
divorced     5201
Name: marital, dtype: int64
```

In [49]:
```
bm1.marital.value_counts(normalize=True).plot.barh()
plt.show()
```



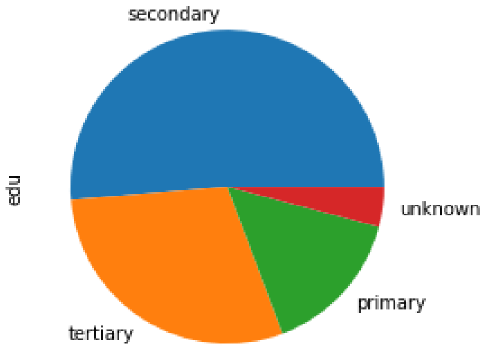
In [48]:
```
##- catergories blood group and male female
```

In [50]:
```
## Which of the two job categories are the least and the most contacted by the bank respectively?

bm1.job.value_counts(normalize=True).plot.barh()
plt.show()

# least- student and Most- Blue-collor
```

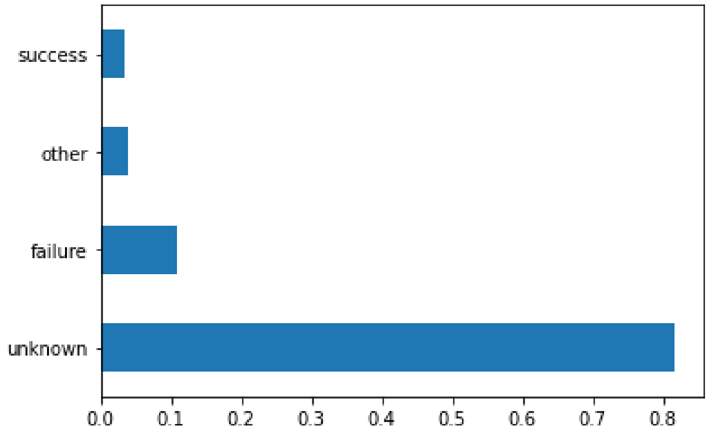


In [51]:
```
### Categorical Ordered Univariate Analysis

## Age, Education, month, response
```

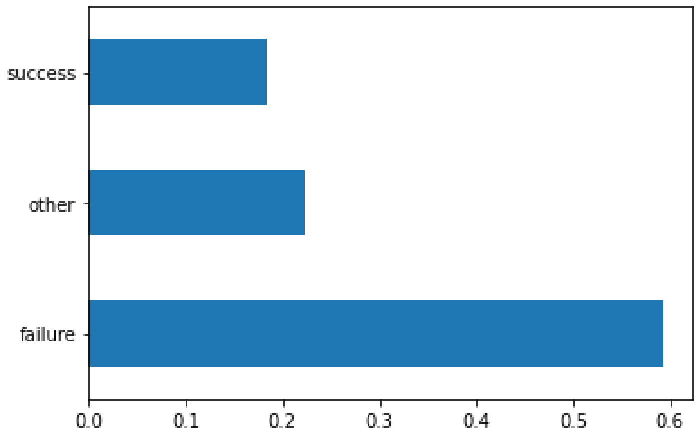
In [51]:
```
# for education

bm1.edu.value_counts(normalize=True).plot.pie()
plt.show()
```



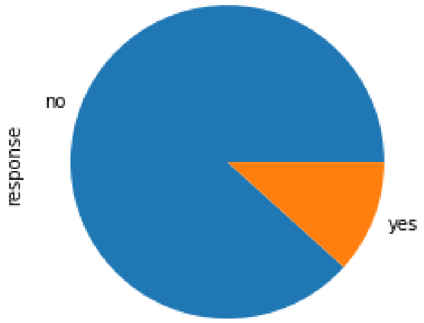
In [52]:
```
# previoues outcome

bm1.poutcome.value_counts(normalize=True).plot.barh()
plt.show()
```



In [53]:
```
# previoues outcome- remove unkonwn

bm1[~(bm1.poutcome=='unknown')].poutcome.value_counts(normalize=True).plot.barh()
plt.show()
```



In [54]:
```
# for response

bm1.response.value_counts(normalize=True).plot.pie()
plt.show()
```



In [61]:
```
#### practice-

# 1- order categorical- dates in year and rating at zomato
#2- salary- draw a histogram, if min in no income then standard is good and vice versa
```

In [55]:
```
print(' EDA-3 bivariate / Multivariate Analysis')
print(' EDA-3 bivariate / Multivariate Analysis')
print(' EDA-3 bivariate / Multivariate Analysis')
print(' EDA-3 bivariate / Multivariate Analysis')
print(' EDA-3 bivariate / Multivariate Analysis')
```

```
 EDA-3 bivariate / Multivariate Analysis
 EDA-3 bivariate / Multivariate Analysis
 EDA-3 bivariate / Multivariate Analysis
 EDA-3 bivariate / Multivariate Analysis
 EDA-3 bivariate / Multivariate Analysis
```

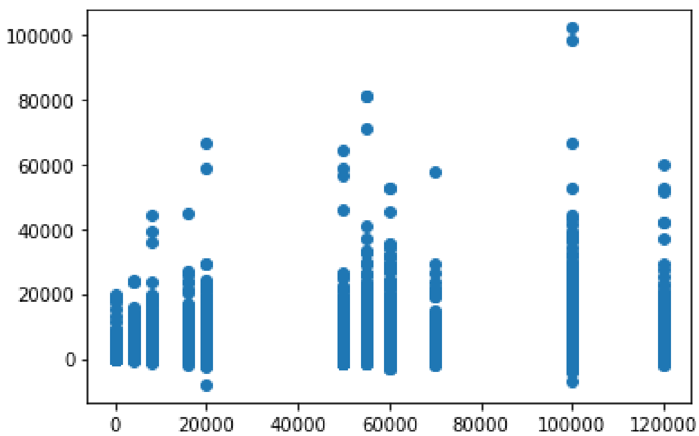
In [63]:
```
## q-1 In the ‘Attribute Dataset’, there is a column named ‘Style’, which contains the different style cat

# Which of the following categories under the ‘Style’ column can be grouped in the ‘Others’ category? Per

# (note: this can have multiple correct answers, select all which fulfil the requirement
```

In [57]:
```
bm1.head(3)
```

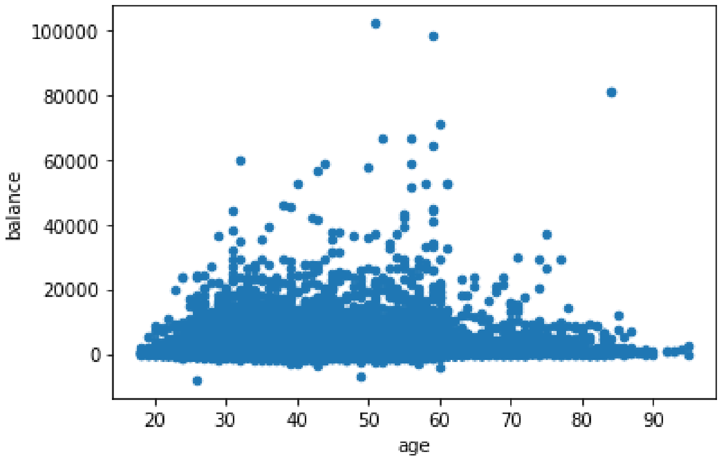
Out[57]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may	4.350000	1	NaN	
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may	2.516667	1	NaN	
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may	1.266667	1	NaN	

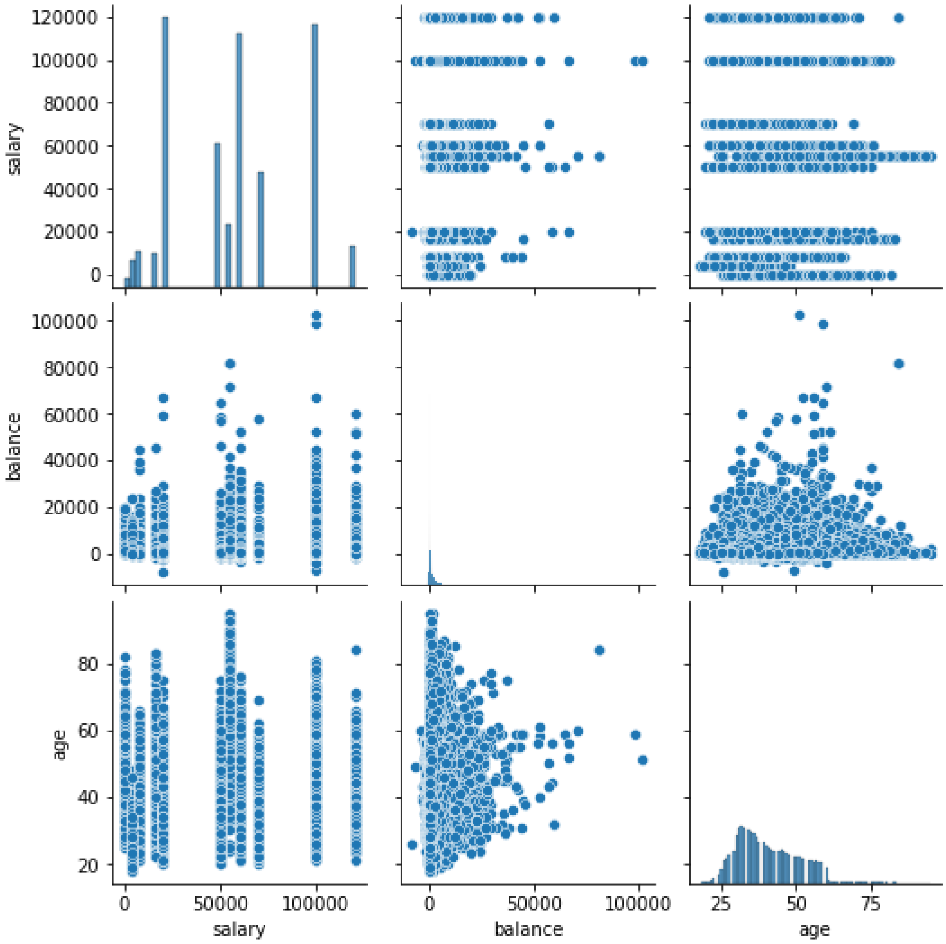
In [59]:
```
## Numeric- Numeric

plt.scatter(bm1.salary, bm1.balance)
plt.show()
```



In [60]:
```
bm1.plot.scatter(x='age', y='balance')
plt.show()
```



In [61]:
```
sns.pairplot(data= bm1, vars=['salary','balance','age'])
plt.show()
```

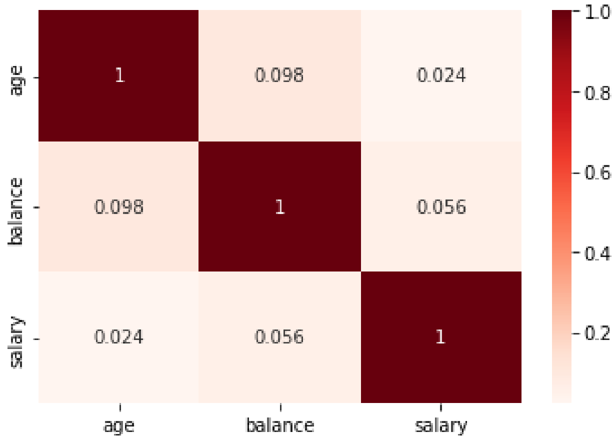


In [62]:
```
## as we coudnt find much relation with these plots, it is better to use Corelation chart. or heat map

bm1[['age','balance','salary']].corr()
```

Out[62]:

	age	balance	salary
age	1.000000	0.097755	0.024374
balance	0.097755	1.000000	0.055505
salary	0.024374	0.055505	1.000000

In [66]:
```
## now plot the heatmap for corelation

sns.heatmap(bm1[['age','balance','salary']].corr(),annot= True, cmap='Reds')
plt.show()
```



In [68]:
```
## Numeric - Catagorical

# eg- catagorical- response, Numercial- age, salary, balance
```

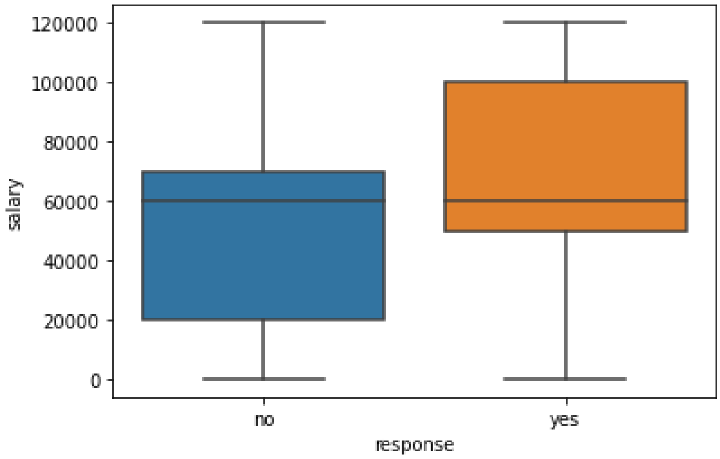
In [69]:
```
# response vs salary

bm1.groupby('response')['salary'].mean()
```

Out[69]:
```
response
no     56769.510482
yes    58780.510880
Name: salary, dtype: float64
```

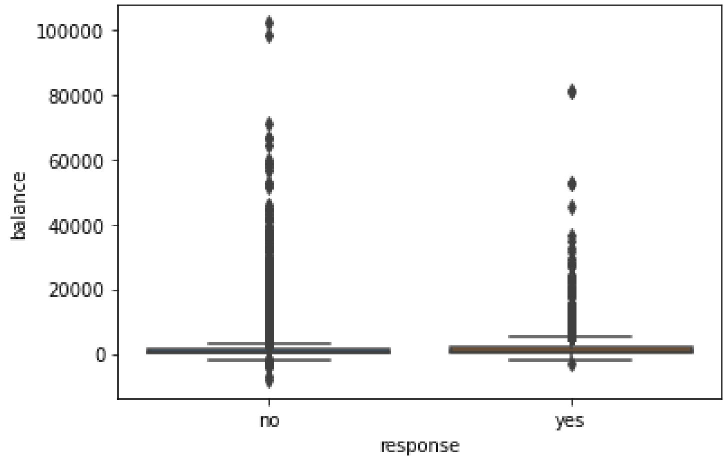
In [70]:
```
bm1.groupby('response')['salary'].median()
```

Out[70]:
```
response
no     60000.0
yes    60000.0
Name: salary, dtype: float64
```

In [71]:
```
## box plot for slary and response

sns.boxplot(data= bm1, x='response', y='salary')
plt.show()
```



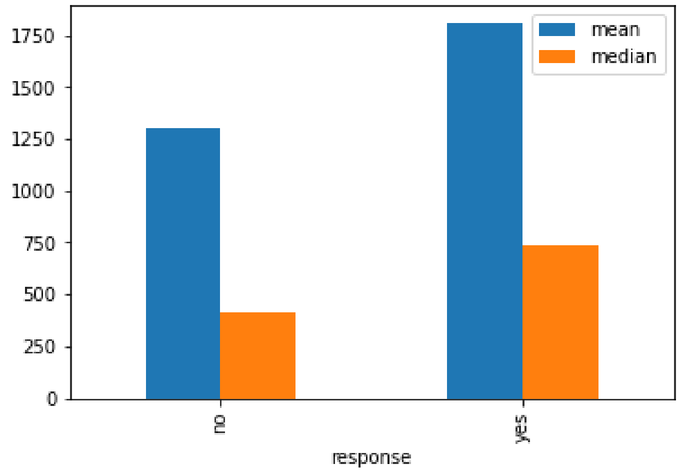
In [72]:
```
## Response vs balance

sns.boxplot(data= bm1, x='response', y='balance')
plt.show()

## nothing is clear from plot
```



In [73]:
```
bm1.groupby('response')['balance'].median()
```

Out[73]:
```
response
no      417.0
yes     733.0
Name: balance, dtype: float64
```

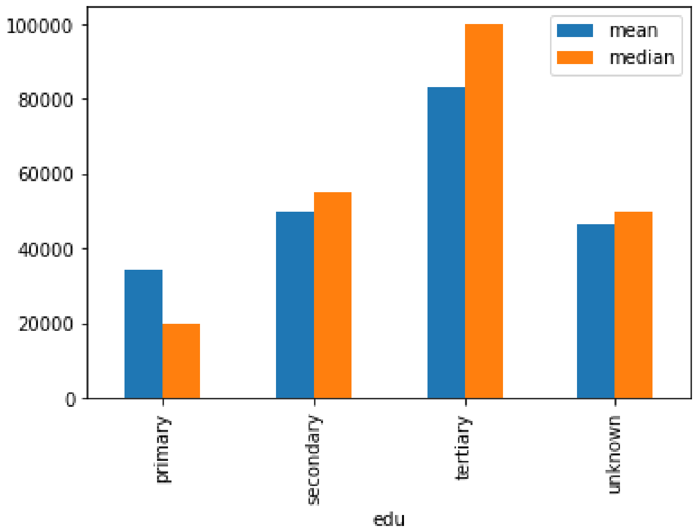
In [80]:
```
bm1.groupby('response')['balance'].aggregate(['mean','median']).plot.bar()
plt.show()
```



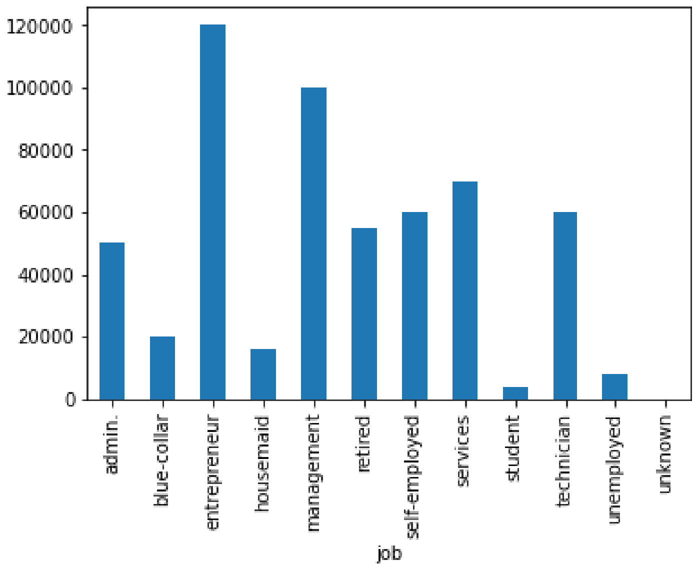
In [86]:
```
bm1.groupby('edu')['response'].value_counts()
```

Out[86]:
```
edu        response
primary    no           6248
           yes           591
secondary  no          20732
           yes          2448
tertiary   no          11292
           yes          1994
unknown    no           1604
           yes           252
Name: response, dtype: int64
```

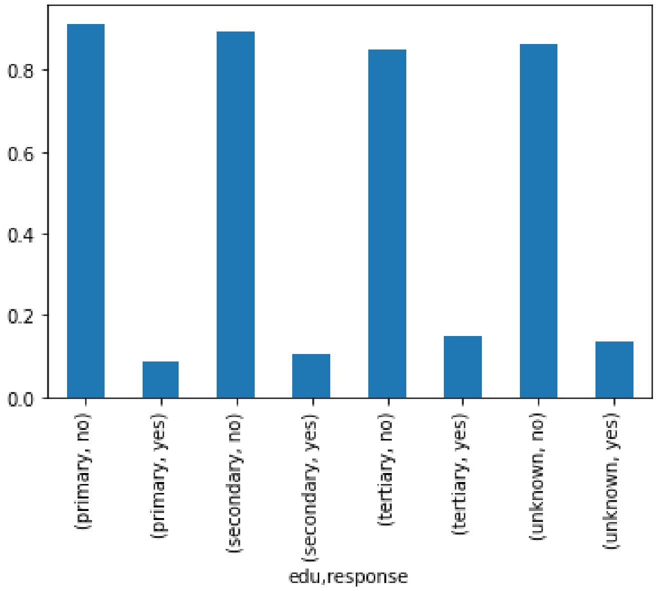
In [85]:
```
## for education vs salary highest mean and least median

bm1.groupby('edu')['salary'].aggregate(['mean','median']).plot.bar()
plt.show()
```



In [91]:
```
bm1.groupby('job')['salary'].mean().plot.bar()
plt.show()
```



In [106…
```
### Catagorical vs Catagorical

# eduvs resonse


## method 1

bm1.groupby('edu')['response'].value_counts(normalize=True).plot.bar()
plt.show()
```



In [108…

```
# method 2

## in response convert yes and no in 1 and 0

bm1['response1']= np.where(bm1.response=='yes',1,0)

bm1.response1.value_counts()
```

Out[108]:

```
0    39906
1     5285
Name: response1, dtype: int64
```

In [109…

```
bm1.response1.value_counts(normalize=True)
```

Out[109]:

```
0    0.883052
1    0.116948
Name: response1, dtype: float64
```

In [110…

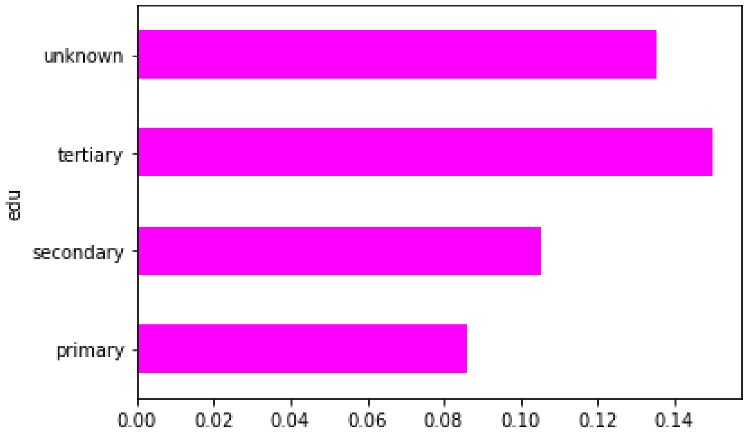
```
bm1.response1.mean()
```

Out[110]:

```
0.11694806488017526
```

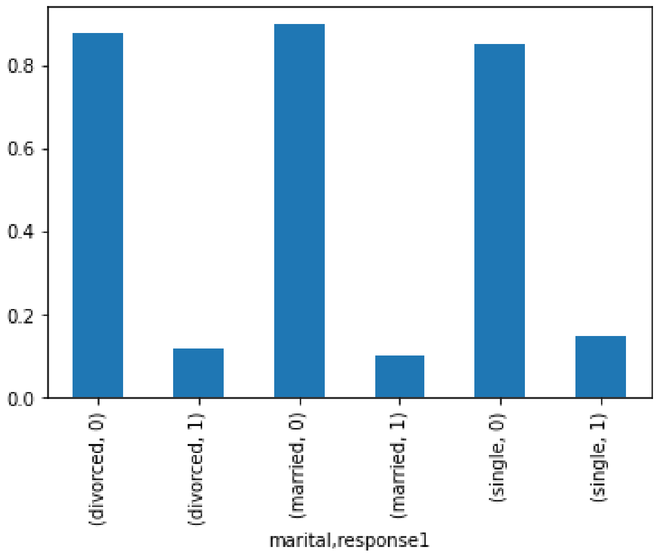
In [139…

```
bm1.groupby('edu')['response1'].mean().plot.barh(color='magenta')
plt.show()
```



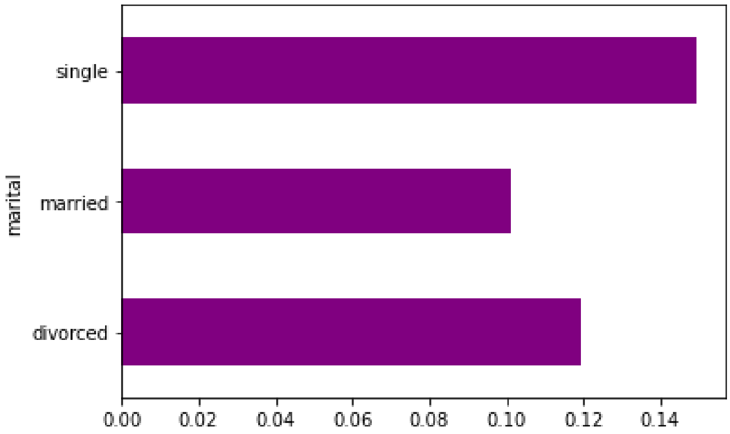
In [117…

```
## Marital vs Response

bm1.groupby('marital')['response1'].value_counts(normalize=True).plot.bar()
plt.show()
```



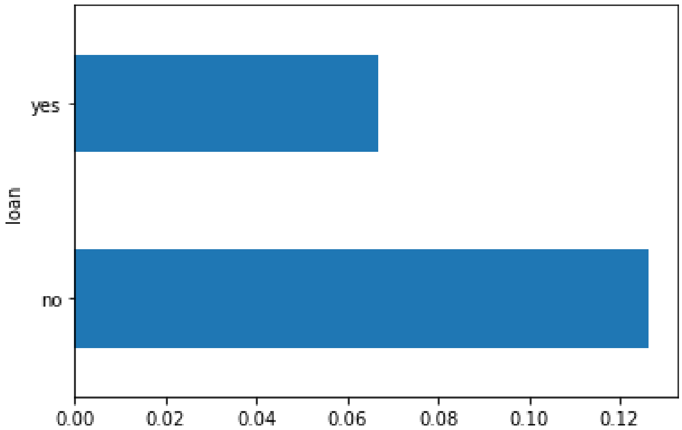
In [136…

```
bm1.groupby('marital')['response1'].mean().plot.barh(color='purple')
plt.show()
```



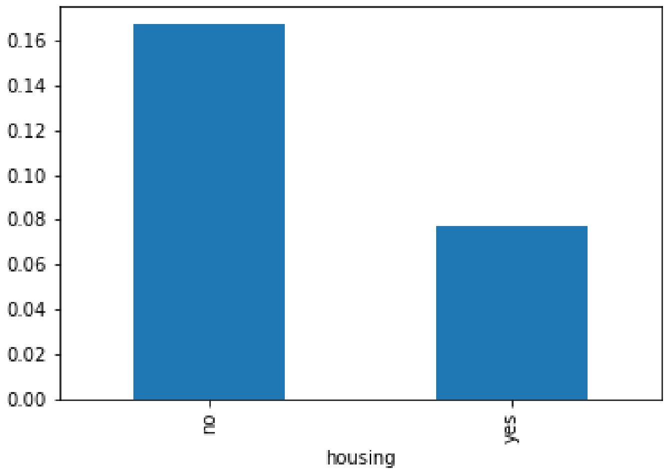
In [118…

```
## Loan vs Response

bm1.groupby('loan')['response1'].mean().plot.barh()
plt.show()
```



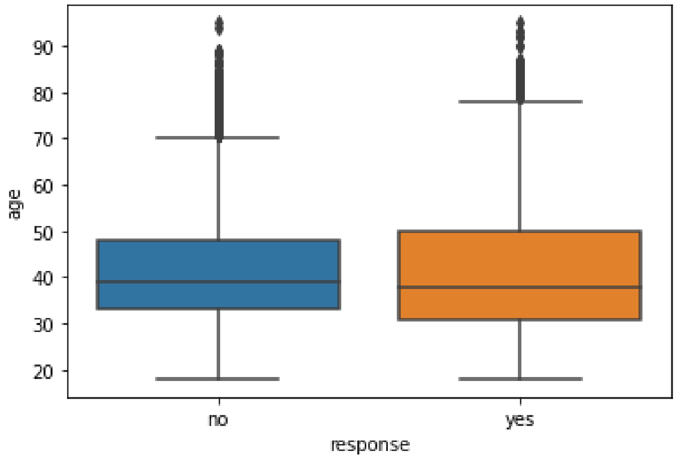
In [120…

```
# hosuing vs response

bm1.groupby('housing')['response1'].mean().plot.bar()
plt.show()
```



In [121…

```
# age vs res

sns.boxplot(data= bm1, x='response', y='age')
plt.show()
```

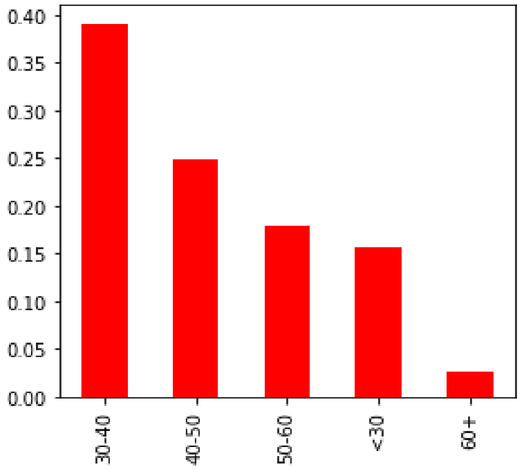


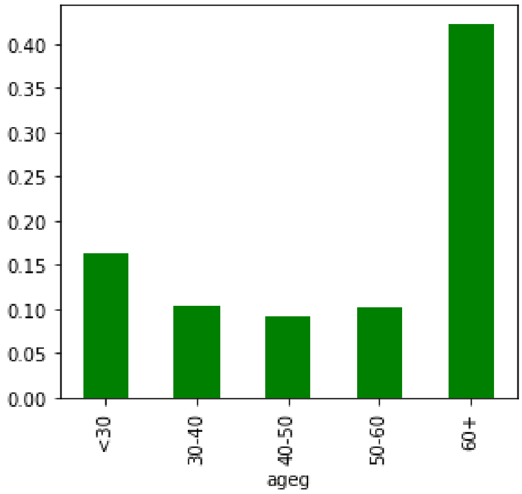
In [125…

```
## craete the bins for age

bm1['ageg']= pd.cut(bm1.age,[0,30,40,50,60,999], labels=['<30','30-40','40-50','50-60','60+'])
```

In [134…

```
plt.figure(figsize=[10,4])
plt.subplot(1,2,1)
bm1.ageg.value_counts(normalize=True).plot.bar(color='red')

plt.subplot(1,2,2)
bm1.groupby('ageg')['response1'].mean().plot.bar(color='green')

plt.show()
```

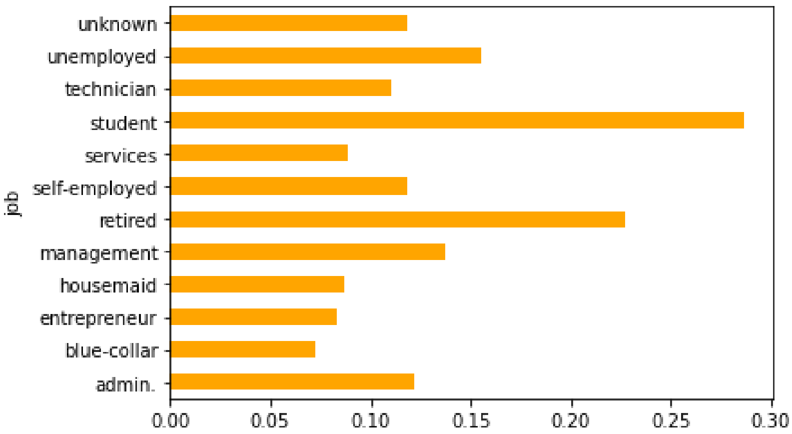




In [135…

```
## job vs response
```

```
bm1.groupby('job')['response1'].mean().plot.barh(color='orange')
plt.show()
```



In [140…

```
### Multivariate

## edu vs marital vs respnse

bm1.response.value_counts(normalize=True)
```

Out[140]:

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

In [141…

```
### center is yes= 0.117
```

In [143…

```
## to analyse such data we need pivot table 2 category and 1 numerical

res= pd.pivot_table(data=bm1, index='edu', columns='marital', values='response1')
res
```

Out[143]:

marital	divorced	married	single
edu			
primary	0.138667	0.075515	0.106808
secondary	0.103485	0.094595	0.129213
tertiary	0.137415	0.129761	0.183546
unknown	0.142012	0.122414	0.162879

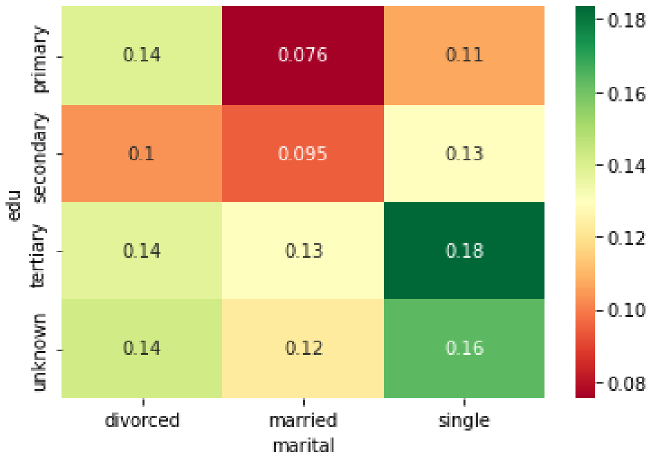
In [148…

```
sns.heatmap(res, annot=True, cmap='summer')
plt.show()

## cmap defines color
```

In [149…

```
## more clarity to define where red is negative , yellow- neutral, green- positive
```

```
sns.heatmap(res, annot=True, cmap='RdYlGn')
plt.show()
```

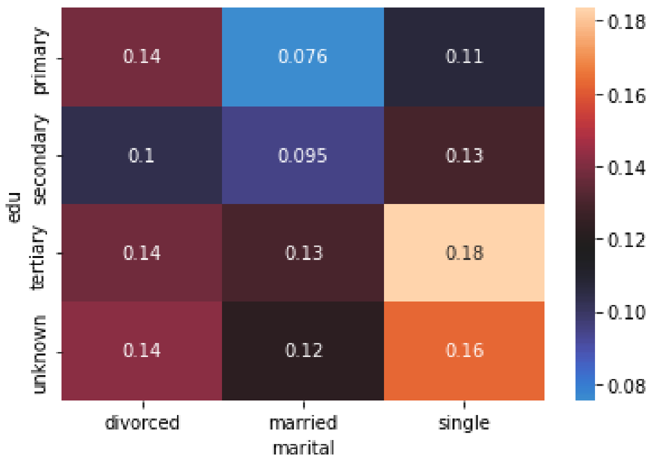


In [151…

```
## Center= overall positive response rate which we get from bm1.response.value_counts(normalize=True) or
# so anything above center is green, lower is red and neutral is yellow

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

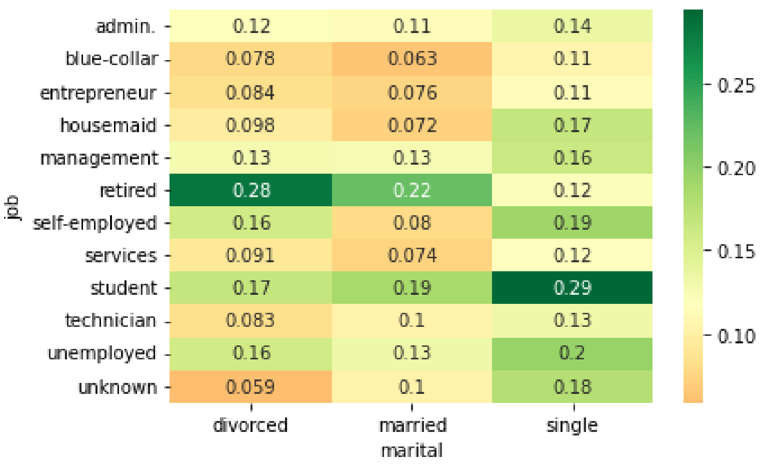
In [152…

```
## without cmap- tough to understand

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



In [158…

```
## Job Vs Marital vs response1

res= pd.pivot_table(data=bm1, index='job', columns='marital', values='response1')

sns.heatmap(res, annot=True, cmap='RdYlGn', center= 0.117)

plt.show()
```



In [162…

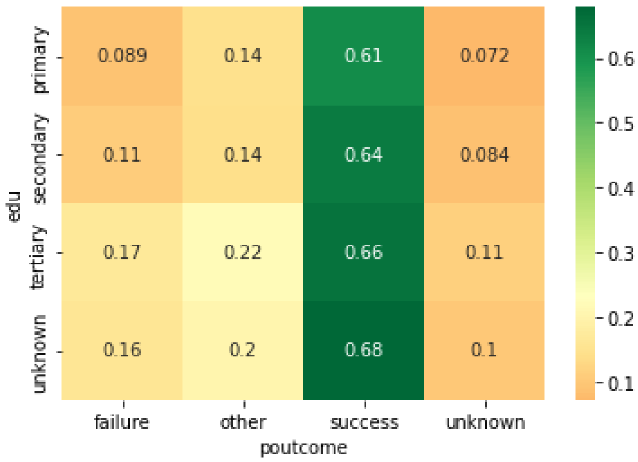
```python
## edu Vs poutcome vs response1

# center for this

bm1[bm1.pdays>0].response1.mean()
```

Out[162]:

```
0.23061076102762967
```

In [165…

```python
## edu Vs poutcome vs response1

res= pd.pivot_table(data=bm1, index='edu', columns='poutcome', values='response1')

sns.heatmap(res, annot=True, cmap='RdYlGn', center= 0.2306)

plt.show()
```



In [ ]: