EDA should be the first step in any data science/machine learning activity.

In [1]:
```
import warnings
warnings.filterwarnings("ignore") # is used in Python to suppress warning messages t
```

In [2]:
```
import pandas as pd, numpy as np
import matplotlib.pyplot as plt, seaborn as sns
%matplotlib inline
#  is a magic command used in Jupyter Notebooks (like in JupyterLab or Google Colab)
# to make matplotlib plots display directly below the code cell that produces them.
```

In [3]:
```
inp = pd.read_csv("bank_marketing_updated_v1.csv")
inp.head()
```

Out[3]:

	banking marketing	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unna
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	
1	customerid	age	salary	balance	marital	jobedu	targeted	d
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	

Step 1: Data Cleaning

In [4]:
```
inp = pd.read_csv("bank_marketing_updated_v1.csv", skiprows=2)
inp.head()
```

Out[4]:

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

Dropping customer id column

In [5]:
```
inp.drop("customerid", axis=1, inplace=True) #axis=1 is for columns.  inplace=true c
inp.head()
```

Out[5]:

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

Divide the jobedu inot job and education

In [6]:
```
inp["job"] = inp.jobedu.apply(lambda x: x.split(",")[0])
inp["education"] = inp.jobedu.apply(lambda x: x.split(",")[1])
inp.drop("jobedu", axis=1,  inplace=True)
inp.head()
```

Out[6]:

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

In [7]:
```
inp.isnull().sum()
```

Out[7]:
```
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
```

Impute/Remove Missing Values

Types of missing values:

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

In [8]:
```
# Creating a clean version of your original DataFrame inp0, named inp1, that contain
# the age column is NOT missing.
inp1 = inp[~inp.age.isnull()].copy()
inp1.shape
```

Out[8]:
```
(45191, 19)
```

In [9]:
```
inp1.age.isnull().sum()
```

Out[9]:
```
0
```

In [10]:
```
# Check if any month entries are float (NaN shows as float)
inp1[inp1['month'].apply(lambda x: isinstance(x, float))].head()
```

Out[10]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month	dura
189	31.0	100000	0	single	no	no	yes	no	unknown	5	NaN	562
769	39.0	20000	245	married	yes	no	yes	no	unknown	7	NaN	148
860	33.0	55000	165	married	yes	no	no	no	unknown	7	NaN	111
1267	36.0	50000	114	married	yes	no	yes	yes	unknown	8	NaN	147
1685	34.0	20000	457	married	yes	no	yes	no	unknown	9	NaN	266

In [11]:
```
inp1.month.value_counts(normalize=True) # is used to display the relative frequency
# normalize=True → instead of counts, it returns proportions
```

Out[11]:
```
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 [12]:
```
month_mode = inp1.month.mode()[0]
month_mode
```

Out[12]:
```
'may, 2017'
```

In [13]:
```
inp1.month.fillna(month_mode, inplace=True)
inp1.month.value_counts(normalize=True)
```

Out[13]:
```
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 [14]:
```
inp1.month.isnull().sum()
```

Out[14]:
```
0
```

In [15]:
```
inp1 = inp1[~inp1['response'].isnull()].copy()
```

In [16]:
```
inp1.response.isnull().sum()
```

Out[16]:
```
0
```

In [17]:
```
inp1.pdays.describe()
```

Out[17]:
```
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 indicate missing values

Our Objectives

1. we want the missing values to be ignored in the calculation.
2. simply make it missing
3. replace -1 with NAN
4. All summary statistics -mean, -median etc. we will ignore the missing values.

In [18]:
```
inp1.loc[inp1.pdays<0, "pdays"] = np.NAN # DataFrame.loc[rows, columns]
inp1.pdays.describe()
```

Out[18]:
```
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
```

Handling Outliers

In [19]:
```
inp1[['age', 'salary', 'balance']].describe()
```

Out[19]:

	age	salary	balance
count	45161.000000	45161.000000	45161.000000
mean	40.935763	57004.849317	1362.850690
std	10.618790	32087.698810	3045.939589
min	18.000000	0.000000	-8019.000000
25%	33.000000	20000.000000	72.000000
50%	39.000000	60000.000000	448.000000
75%	48.000000	70000.000000	1428.000000
max	95.000000	120000.000000	102127.000000

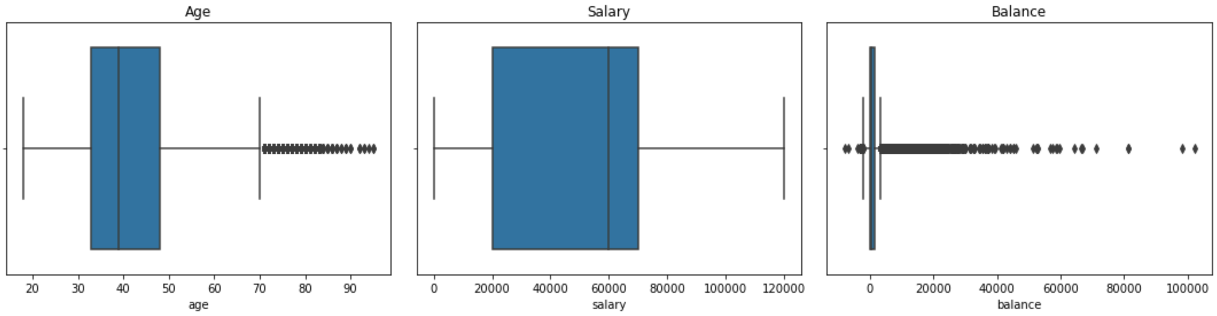
In [20]:
```
fig, axes = plt.subplots(1, 3, figsize=(15, 4))  # 1 row, 3 columns

sns.boxplot(ax=axes[0], x=inp1['age'])
axes[0].set_title('Age')

sns.boxplot(ax=axes[1], x=inp1['salary'])
axes[1].set_title('Salary')

sns.boxplot(ax=axes[2], x=inp1['balance'])
axes[2].set_title('Balance')

plt.tight_layout()
plt.show()
```



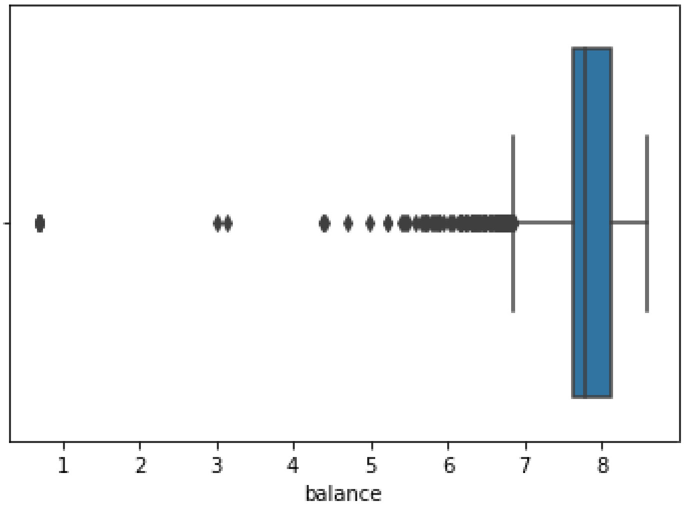
In [21]:
```
Q1 = inp1['balance'].quantile(0.25)
Q3 = inp1['balance'].quantile(0.75)
IQR = Q3 - Q1

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

inp1['balance'] = inp1['balance'].clip(lower, upper)
```

In [22]:
```
shift = abs(inp1['balance'].min()) + 1
inp1['balance'] = np.log1p(inp1['balance'] + shift)
```

In [23]:
```
sns.boxplot(x=inp1['balance'])
plt.show()
```



Standardising Values

- Standardization (a type of feature scaling) makes your numeric columns:
- Mean = 0
- Standard deviation = 1

- This is important for many machine learning algorithms (like logistic regression, SVM, KNN, neural networks), which are sensitive to scale. You can standardize numeric column but not Boolean or Categorial.

Duration variable

In [24]:
```
inp1.duration.head()
```

Out[24]:
```
0    261 sec
1    151 sec
2     76 sec
3     92 sec
4    198 sec
Name: duration, dtype: object
```

In [25]:
```
inp1.duration.describe()
```

Out[25]:
```
count       45161
unique       2646
top       1.5 min
freq          138
Name: duration, dtype: object
```

In [26]:
```
inp1.duration.apply(lambda x : float(x.split()[0])/60)
```

Out[26]:
```
0        4.350000
1        2.516667
2        1.266667
3        1.533333
4        3.300000
           ...
45206    0.271389
45207    0.126667
```

```
45208    0.313056
45209    0.141111
45210    0.100278
Name: duration, Length: 45161, dtype: float64
```

In [27]:
```
inp1.duration.apply(lambda x : float(x.split()[0])/60 if x.find('sec')>0 else float(
```

Out[27]:
```
0         4.350000
1         2.516667
2         1.266667
3         1.533333
4         3.300000
            ...
45206    16.283333
45207     7.600000
45208    18.783333
45209     8.466667
45210     6.016667
Name: duration, Length: 45161, dtype: float64
```

In [28]:
```
inp1.duration = inp1.duration.apply(lambda x : float(x.split()[0])/60 if x.find('sec
```

In [29]:
```
inp1.duration.describe()
```

Out[29]:
```
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
```

Step2: Univariate Analysis

In [30]:
```
inp1.dtypes
```

Out[30]:
```
age          float64
salary         int64
balance      float64
marital       object
targeted      object
default       object
housing       object
loan          object
contact       object
day            int64
month         object
duration     float64
campaign       int64
pdays        float64
previous       int64
poutcome      object
response      object
job           object
education     object
dtype: object
```

Marital

In [31]:
```
inp1.marital.value_counts()
```

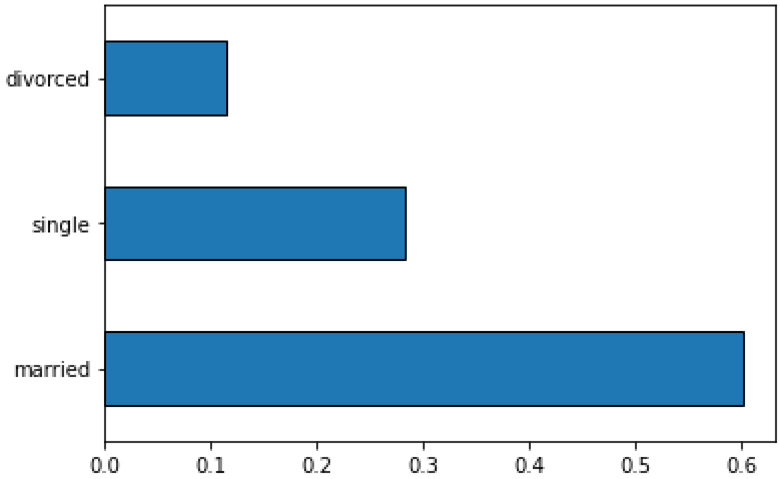
Out[31]:
```
married     27185
single      12778
```

```
divorced     5198
Name: marital, dtype: int64
```

In [32]:
```
inp1.marital.value_counts(normalize=True) # for percentage vise distribution
```

Out[32]:
```
married     0.601957
single      0.282943
divorced    0.115099
Name: marital, dtype: float64
```

In [33]:
```
inp1.marital.value_counts(normalize=True).plot.barh(edgecolor ='black') # horizontal
plt.show()
```



Education

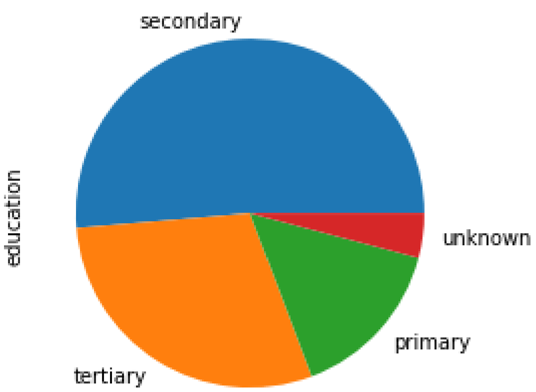
In [34]:
```
inp1.education.value_counts()
```

Out[34]:
```
secondary    23180
tertiary     13286
primary       6839
unknown       1856
Name: education, dtype: int64
```

In [35]:
```
inp1.education.value_counts(normalize=True)
```

Out[35]:
```
secondary    0.513275
tertiary     0.294192
primary      0.151436
unknown      0.041097
Name: education, dtype: float64
```

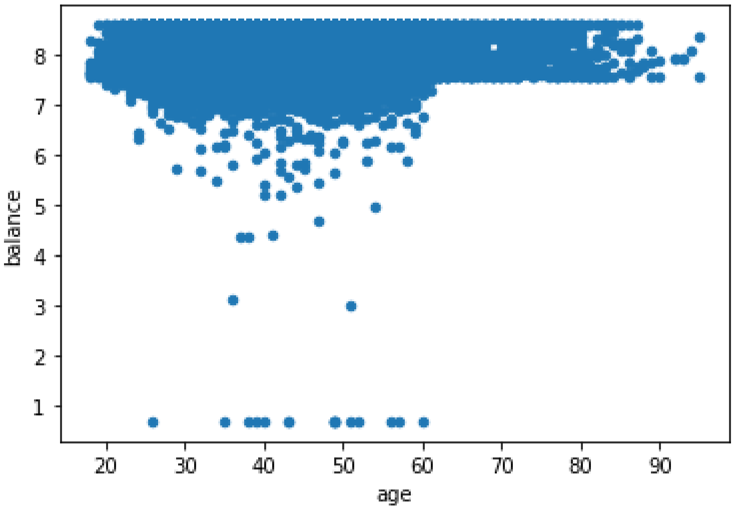
In [36]:
```
inp1.education.value_counts(normalize=True).plot.pie()
plt.show()
```



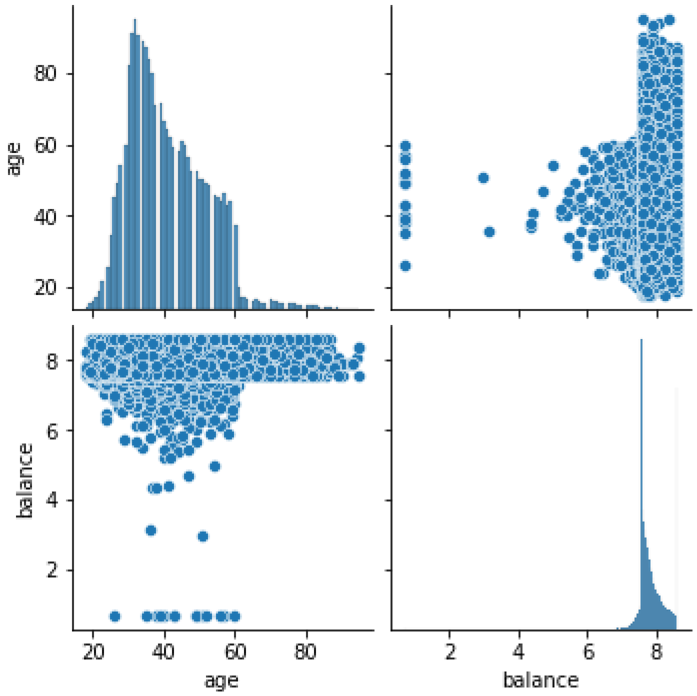
Step 3: Bi-variate analysis

Numerical-Numerical

In [37]:
```
inp1.plot.scatter(x="age", y="balance")
plt.show()
```



In [38]:
```
sns.pairplot(data=inp1, vars=["age", "balance"])
plt.show()
```



Quantifying using correlation values

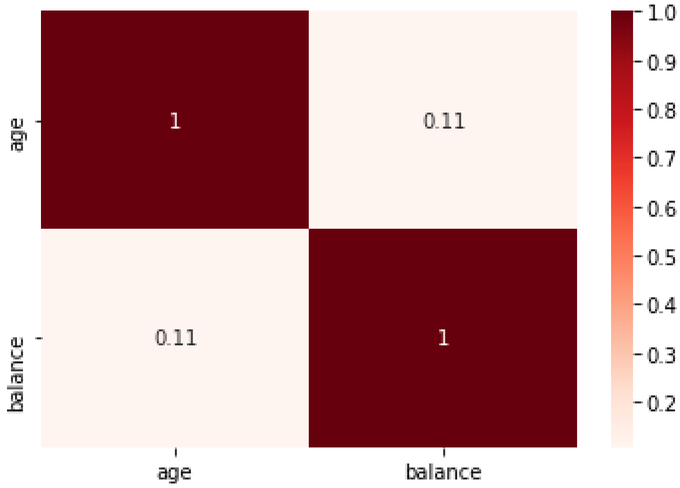
In [39]:
```
inp1[["age","balance"]].corr()  # Double square brackets → multiple columns
```

Out[39]:

	age	balance
age	1.000000	0.106529
balance	0.106529	1.000000

Correlation heatmap

In [40]:
```
sns.heatmap(inp1[["age", "balance"]].corr(), annot=True, cmap="Reds")
plt.show()
```



Correlation vs Causation

Numerical - Categorical Analysis

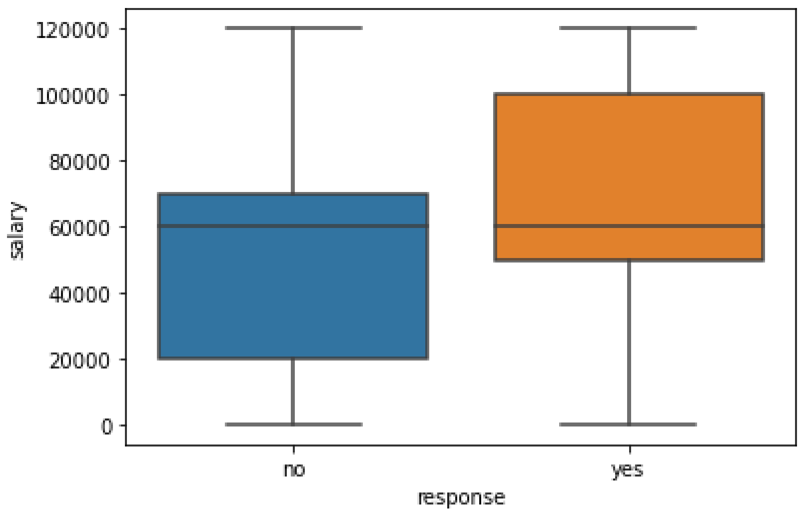
In [41]:
```
inp1.groupby("response")["salary"].mean()
```

Out[41]:
```
response
no     56769.510482
yes    58780.510880
Name: salary, dtype: float64
```

In [42]:
```
inp1.groupby("response")["salary"].median()
```

Out[42]:
```
response
no     60000
yes    60000
Name: salary, dtype: int64
```

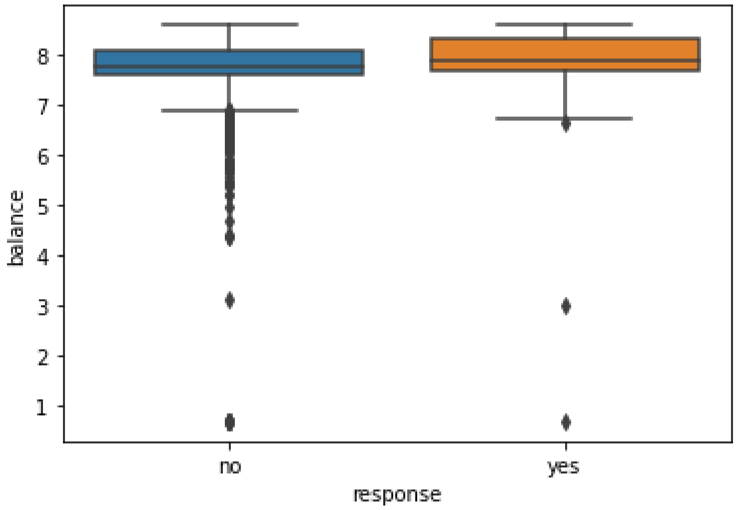
In [43]:
```
sns.boxplot(data=inp1, x="response", y="salary")
plt.show()
```



Response vs. Balance

we know that balance is highly skewed - has very high values

In [44]:
```
sns.boxplot(data=inp1, x="response", y="balance")
plt.show()
```



In [45]:
```
inp1.groupby("response")["balance"].mean() # note the different brackets in groupby
# round brackets ( ): used for the argument to the groupby() function.
# square brackets [ ]: used for selecting a column from the grouped data.
```

Out[45]:
```
response
no     7.884147
yes    7.997069
Name: balance, dtype: float64
```

In [46]:
```
inp1.groupby("response")["balance"].median()
```

Out[46]:
```
response
no     7.775276
yes    7.899895
Name: balance, dtype: float64
```

75th percentile

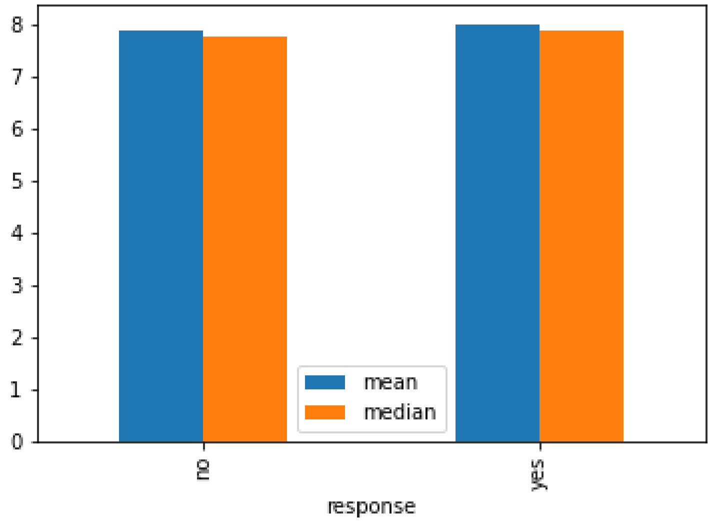
In [47]:
```
def p75(x):
    return np.quantile(x, 0.75)
```

In [48]:
```
inp1.groupby("response")["balance"].aggregate(["mean","median",p75])
```

Out[48]:

response	mean	median	p75
no	7.884147	7.775276	8.104401
yes	7.997069	7.899895	8.324336

In [49]:
```
inp1.groupby("response")["balance"].aggregate(["mean","median"]).plot.bar()
plt.show()
```



Categorical - Categorical Analysis

In [50]:
```
inp1["response_flag"] = np.where(inp1.response=="yes",1,0)
```

In [51]:
```
inp1.response_flag.value_counts()
```

Out[51]:
```
0    39876
1     5285
Name: response_flag, dtype: int64
```

In [52]:
```
inp1.response.value_counts()
```

Out[52]:
```
no     39876
yes     5285
Name: response, dtype: int64
```

In [53]:
```
inp1.response.value_counts(normalize=True)
```

Out[53]:
```
no     0.882974
yes    0.117026
Name: response, dtype: float64
```

In [54]:
```
inp1.response_flag.mean()
```

Out[54]:
```
0.1170257523084077
```

Education vs. Response rate

In [55]:
```
inp1.groupby("education")["response_flag"].mean()
```

Out[55]:
```
education
primary      0.086416
secondary    0.105608
tertiary     0.150083
unknown      0.135776
Name: response_flag, dtype: float64
```

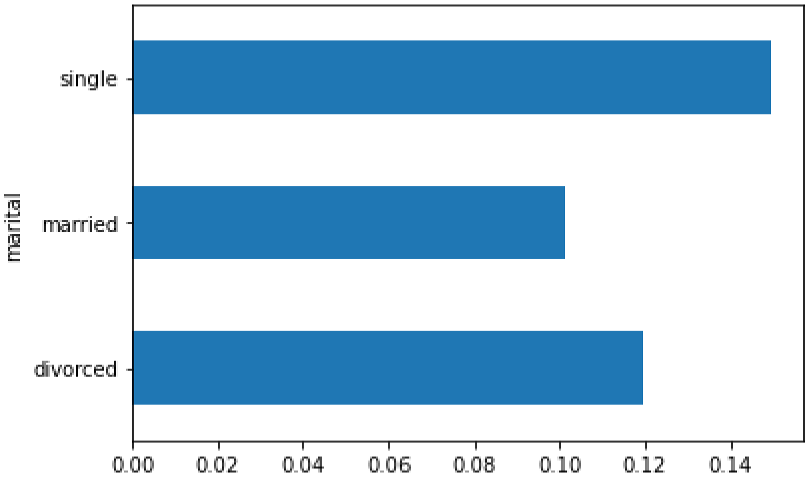
Marital vs. Response rate

In [56]:
```
inp1.groupby("marital")["response_flag"].mean()
```

Out[56]:
```
marital
divorced    0.119469
married     0.101269
```

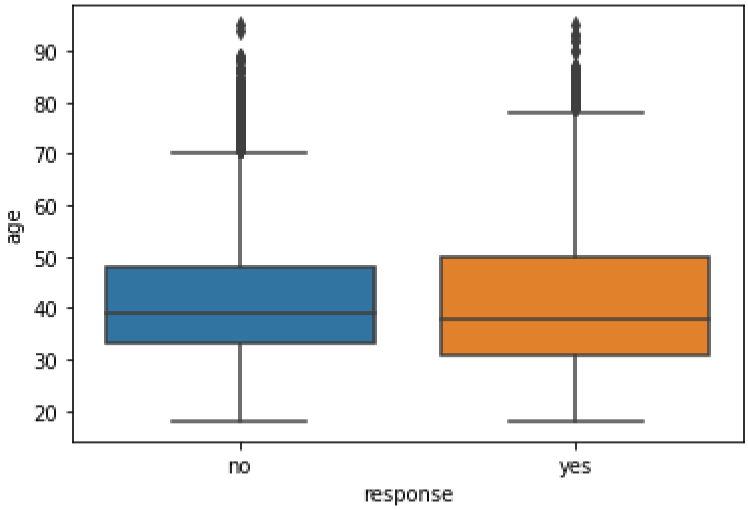
```
single      0.149554
Name: response_flag, dtype: float64
```

In [57]:
```
inp1.groupby("marital")["response_flag"].mean().plot.barh()
plt.show()
```



Age Vs. Response

In [58]:
```
sns.boxplot(data=inp1, x="response", y="age")
plt.show()
```



Making bucket from the age column

In [59]:
```
pd.cut(inp1.age, [0,30,40,50,60,9999], labels=["<30","30-40","40-50","50-60", "60+"]
```

Out[59]:
```
0        50-60
1        40-50
2        30-40
3        40-50
4        30-40
         ...
45206    50-60
45207      60+
45208      60+
45209    50-60
45210    30-40
Name: age, Length: 45161, dtype: category
Categories (5, object): ['<30' < '30-40' < '40-50' < '50-60' < '60+']
```

In [60]:
```
inp1.age.head()
```

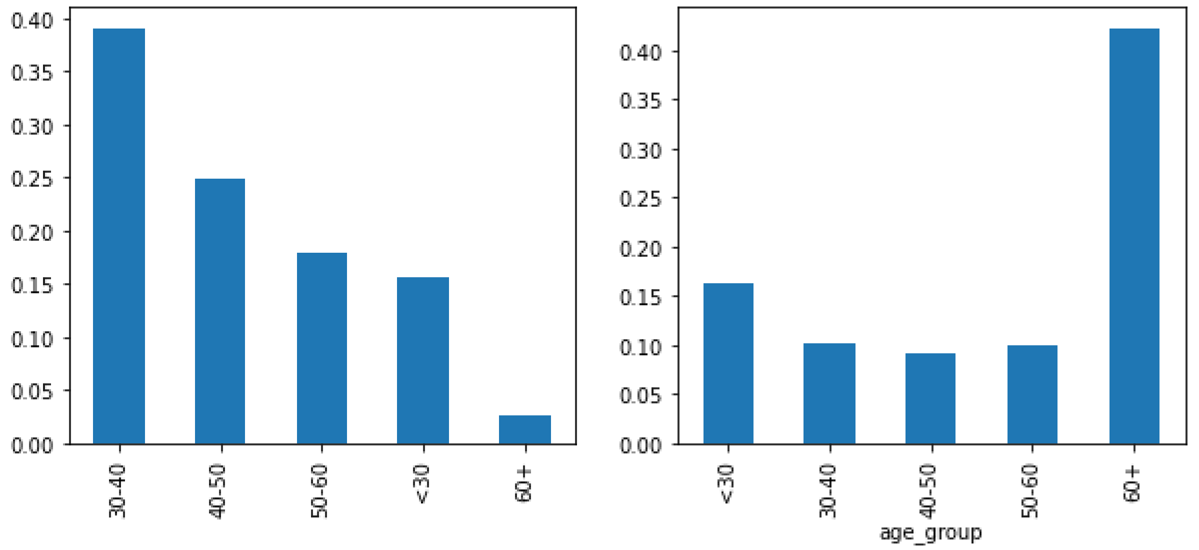
Out[60]:
```
0    58.0
1    44.0
2    33.0
3    47.0
4    33.0
Name: age, dtype: float64
```

In [61]:
```
inp1["age_group"] = pd.cut(inp1.age, [0,30,40,50,60,9999], labels=["<30","30-40","40
```

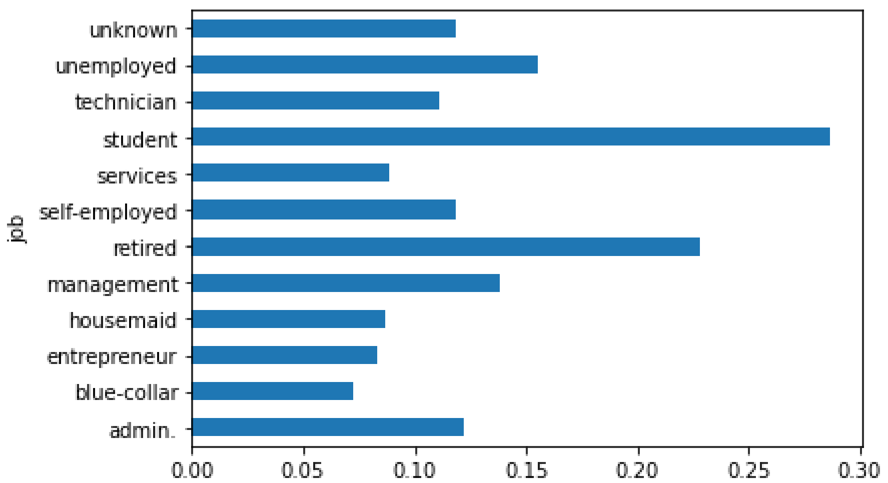
In [62]:
```
inp1.age_group.value_counts(normalize=True)
```

Out[62]:
```
30-40    0.391090
40-50    0.248688
50-60    0.178406
<30      0.155555
60+      0.026262
Name: age_group, dtype: float64
```

In [63]:
```
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 [64]:
```
inp1.groupby(["job"])["response_flag"].mean().plot.barh()
plt.show()
```



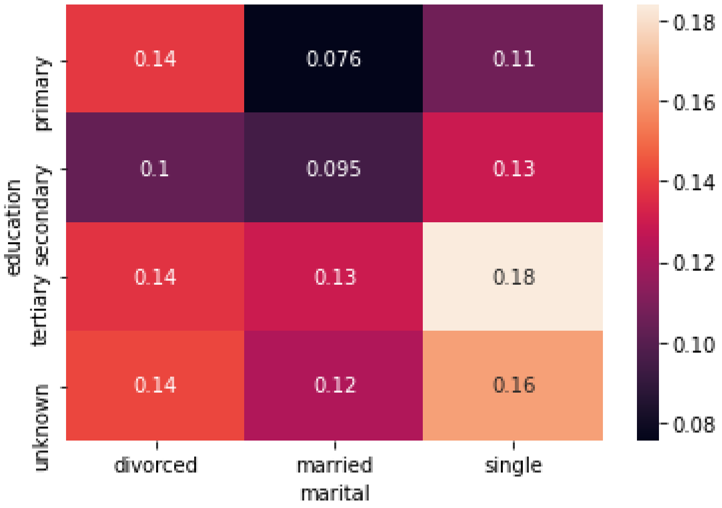
Step 3: Multivariate Analysis

In [65]:
```
res = pd.pivot_table(data=inp1, index="education", columns="marital", values="respon
res
```

Out[65]:

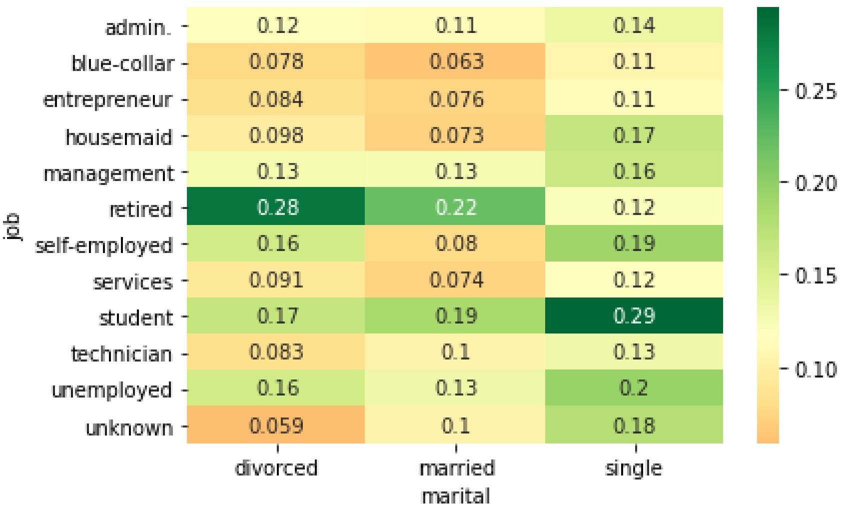
marital education	divorced	married	single
primary	0.138852	0.075601	0.106808
secondary	0.103559	0.094650	0.129271
tertiary	0.137415	0.129835	0.183737
unknown	0.142012	0.122519	0.162879

In [66]:
```
sns.heatmap(res, annot=True)
plt.show()
```



Job vs. Marital Vs. Response

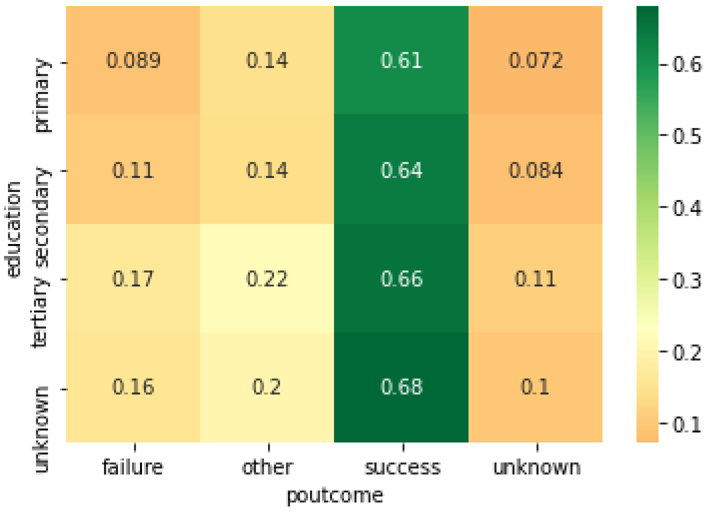
In [67]:
```
res = pd.pivot_table(data=inp1, index="job", columns="marital", values="response_fla
sns.heatmap(res, annot=True, cmap="RdYlGn", center=0.117)
plt.show()
```



In [68]:
```
inp1[inp1.pdays>0].response_flag.mean() # calculating the center value i.e. mean val
```

Out[68]: 0.2307785593014795

In [69]:
```
res = pd.pivot_table(data=inp1, index="education", columns="poutcome", values="respo
sns.heatmap(res, annot=True, cmap="RdYlGn", center=0.2306) # inserting the actual ce
plt.show()
```



In [ ]:

In [ ]: