BANK-MARKETING PREDICTION

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
color = sns.color_palette()
import os
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
bk_df=pd.read_csv("C:/Users/yuvak/OneDrive/Desktop/bank-marketing.csv")
```

In [3]:

```
bk_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 19 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   salary     45211 non-null  int64 
 3   marital    45211 non-null  object
 4   education  45211 non-null  object
 5   targeted   45211 non-null  object
 6   default    45211 non-null  object
 7   balance    45211 non-null  int64 
 8   housing    45211 non-null  object
 9   loan       45211 non-null  object
 10  contact    45211 non-null  object
 11  day        45211 non-null  int64 
 12  month      45211 non-null  object
```

```
 13  duration   45211 non-null  int64
 14  campaign   45211 non-null  int64
 15  pdays      45211 non-null  int64
 16  previous   45211 non-null  int64
 17  poutcome   45211 non-null  object
 18  response   45211 non-null  object
dtypes: int64(8), object(11)
memory usage: 6.6+ MB
```

In [4]:

```
bk_df.head()
```

Out[4]:

	age	job	salary	marital	education	targeted	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	response
0	58	management	100000	married	tertiary	yes	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	60000	single	secondary	yes	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	120000	married	secondary	yes	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	20000	married	unknown	no	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	0	single	unknown	no	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

Basic data observation

In [5]:

#shape of the data
bk_df.shape

Out[5]:

```
(45211, 19)
```

In [6]:

bk_df.describe()

Out[6]:

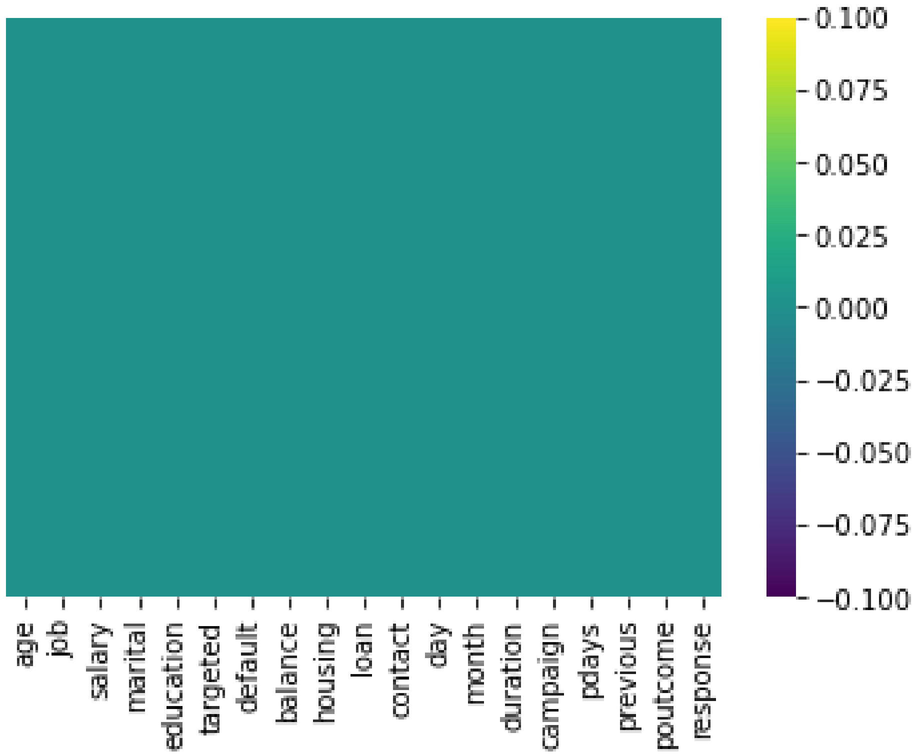
	age	salary	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	57006.171065	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.618762	32085.718415	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	0.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	20000.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	60000.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	70000.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	120000.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

In [8]:

```
sns.heatmap(bk_df.isnull(),yticklabels=False,cbar=True,cmap='viridis',color="green")
```

Out[8]:

```
<AxesSubplot:>
```



Describe the pdays column, make note of the mean, median and minimum values. Anything fishy in the values?

In [9]:

```
bk_df['pdays'].describe()
```

Out[9]:

```
count    45211.000000
mean        40.197828
std        100.128746
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

In [10]:

```python
print("Mean:",bk_df['pdays'].mean())
print("Median:",bk_df['pdays'].median())
print("mode:",bk_df['pdays'].mode()[0])
```

```
Mean: 40.19782796222158
Median: -1.0
mode: -1
```

Describe the pdays column again, this time limiting yourself to the relevant values of pdays. How different are the mean and the median values?

In [12]:

```python
print("Mean of pdays column after eliminating -1 values is", bk_df[bk_df['pdays'] != -1]['pdays'].mean())
print("Median of pdays column after eliminating -1 values is", bk_df[bk_df['pdays'] != -1]['pdays'].median())
```

```
Mean of pdays column after eliminating -1 values is 224.57769165556496
Median of pdays column after eliminating -1 values is 194.0
```

First, perform bi-variate analysis to identify the features that are directly associated with the target variable.

.Convert the response variable to a convenient form .Make suitable plots for associations with numerical features and categorical features’

In [13]:

```python
def impute_response(x):
    if x=='yes':
        return 1
    if x=='no':
        return 0

bk_df['response']=bk_df['response'].apply(impute_response)
bk_df['response'].value_counts()
```

Out[13]:

```
0    39922
1     5289
Name: response, dtype: int64
```

In [14]:

```
# here we are seperating categorical and numerical data types
cat_col = []
num_col = []
for col in bk_df.columns:
    if bk_df[col].dtype=='O':
        cat_col.append(col)
    else:
        num_col.append(col)

print("Categorical features : ",cat_col)
print("Numerical features : ",num_col)
```

```
Categorical features :  ['job', 'marital', 'education', 'targeted', 'defaul
t', 'housing', 'loan', 'contact', 'month', 'poutcome']
Numerical features :  ['age', 'salary', 'balance', 'day', 'duration', 'camp
aign', 'pdays', 'previous', 'response']
```

Categorical features

In [15]:

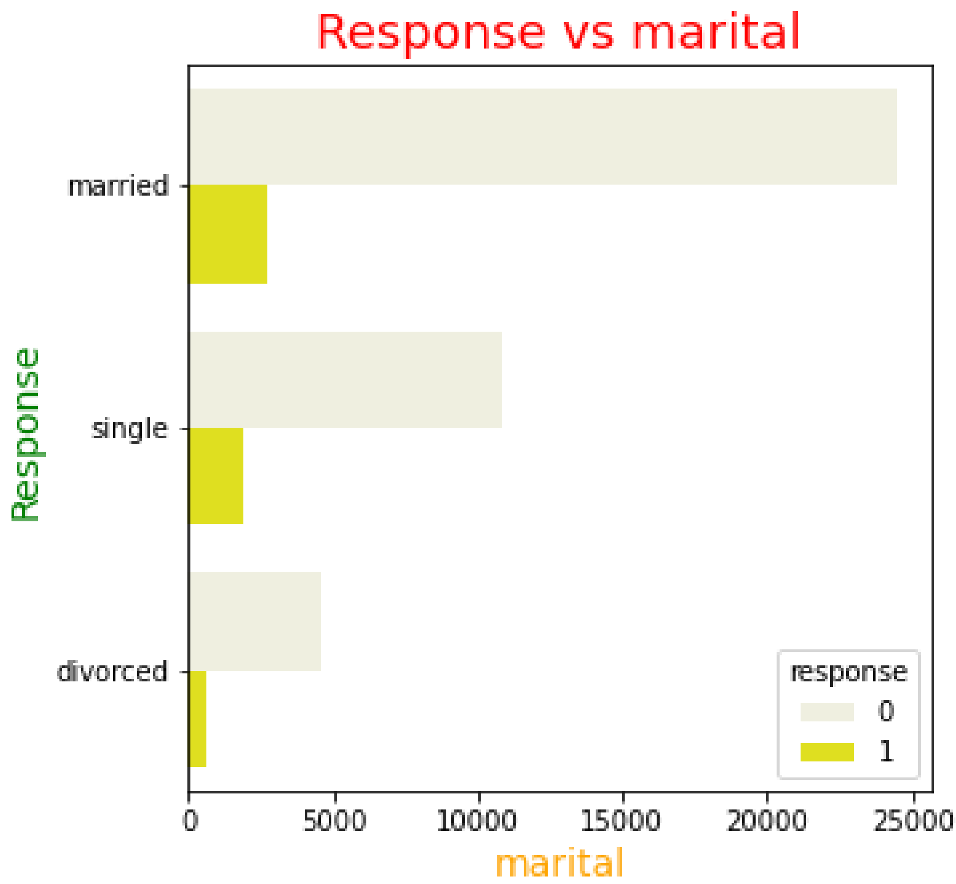
```
for col in cat_col[1:]:
    print(bk_df[col].value_counts())
```

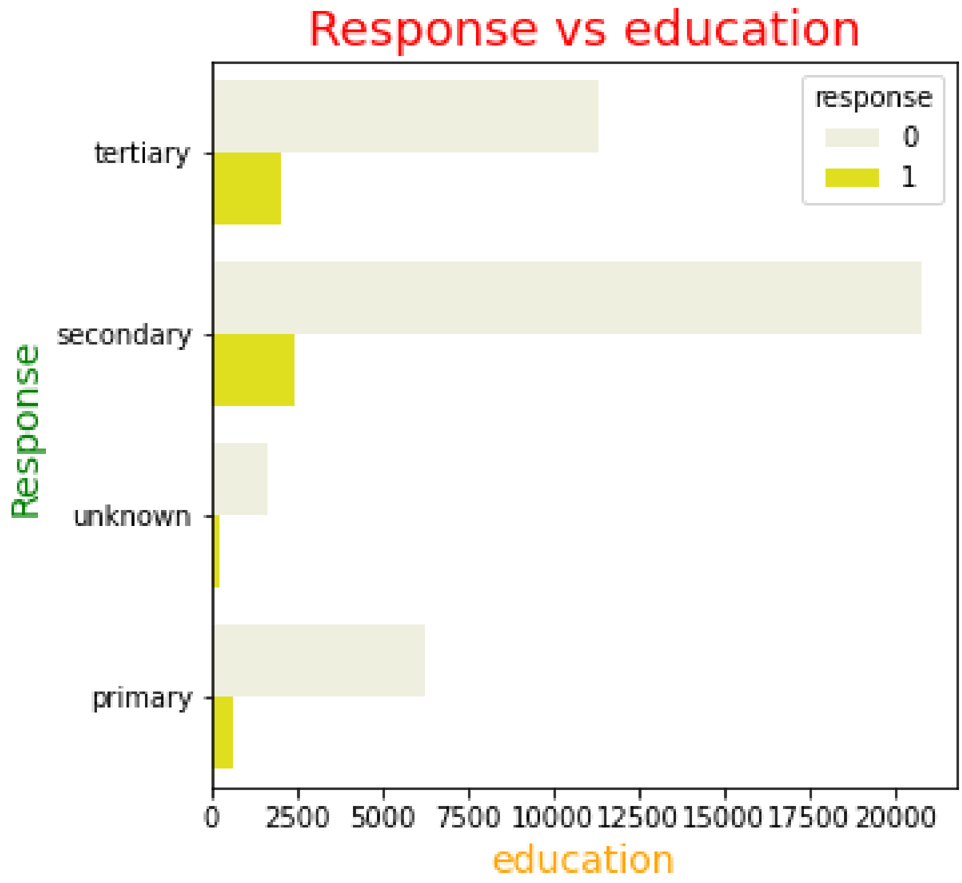
```
married      27214
single       12790
divorced      5207
Name: marital, dtype: int64
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64
yes    37091
no      8120
Name: targeted, dtype: int64
no     44396
yes      815
Name: default, dtype: int64
yes    25130
no     20081
Name: housing, dtype: int64
no     37967
yes     7244
```

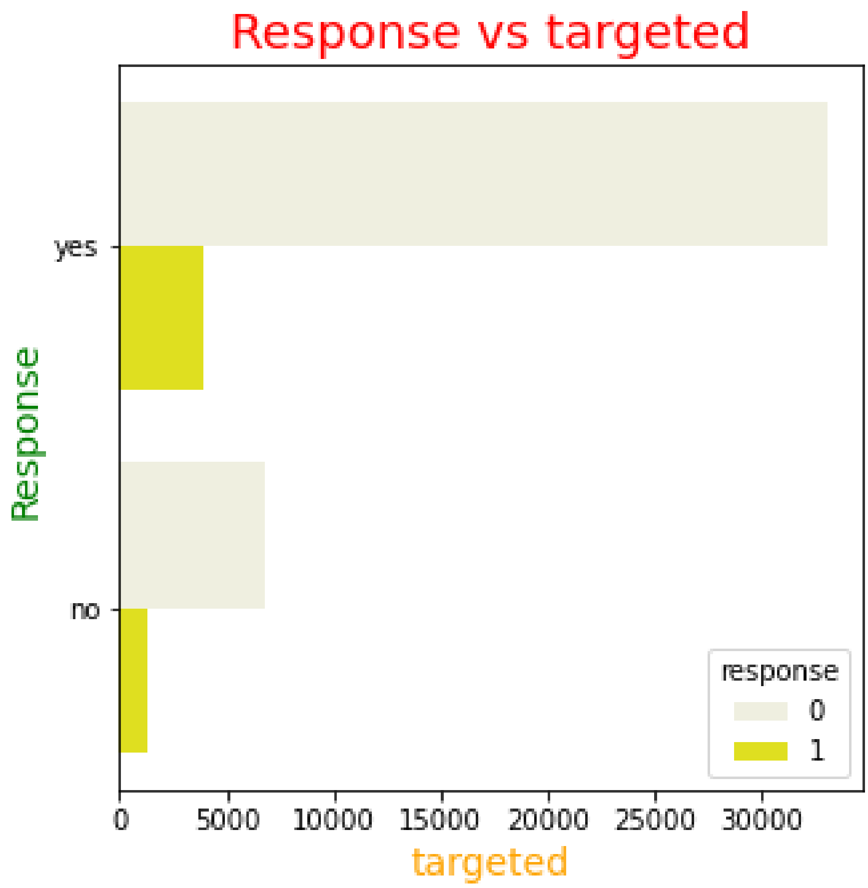
```
Name: loan, dtype: int64
cellular     29285
unknown      13020
telephone     2906
Name: contact, dtype: int64
may    13766
jul     6895
aug     6247
jun     5341
nov     3970
apr     2932
feb     2649
jan     1403
oct      738
sep      579
mar      477
dec      214
Name: month, dtype: int64
unknown    36959
failure     4901
other       1840
success     1511
Name: poutcome, dtype: int64
```

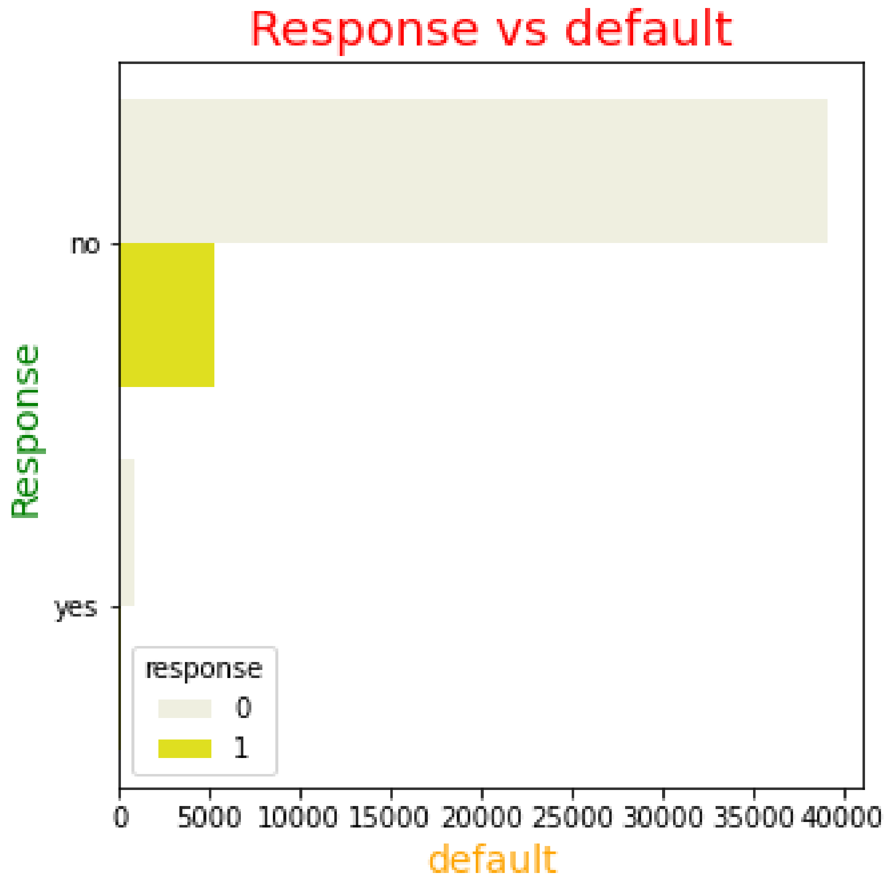
In [32]:

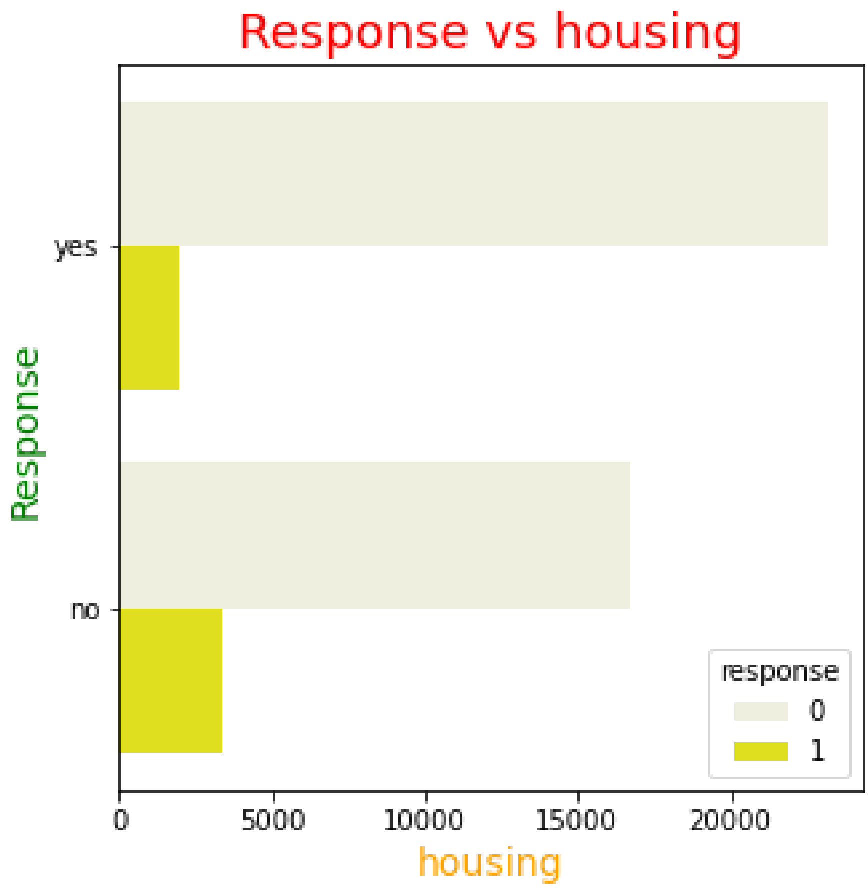
```python
for col in cat_col[1:]:
    plt.figure(figsize=(5,5))
    sns.countplot(y=bk_df[col],hue=bk_df["response"],color="yellow")
    plt.title("Response vs "+col,fontsize=18,color="Red")
    plt.xlabel(col,fontsize=14,color="orange")
    plt.ylabel("Response",fontsize=14,color="green")
    plt.show()
```


Response vs marital
married
single
divorced
response
0
1
0
5000
10000
15000
20000
25000
marital
Response

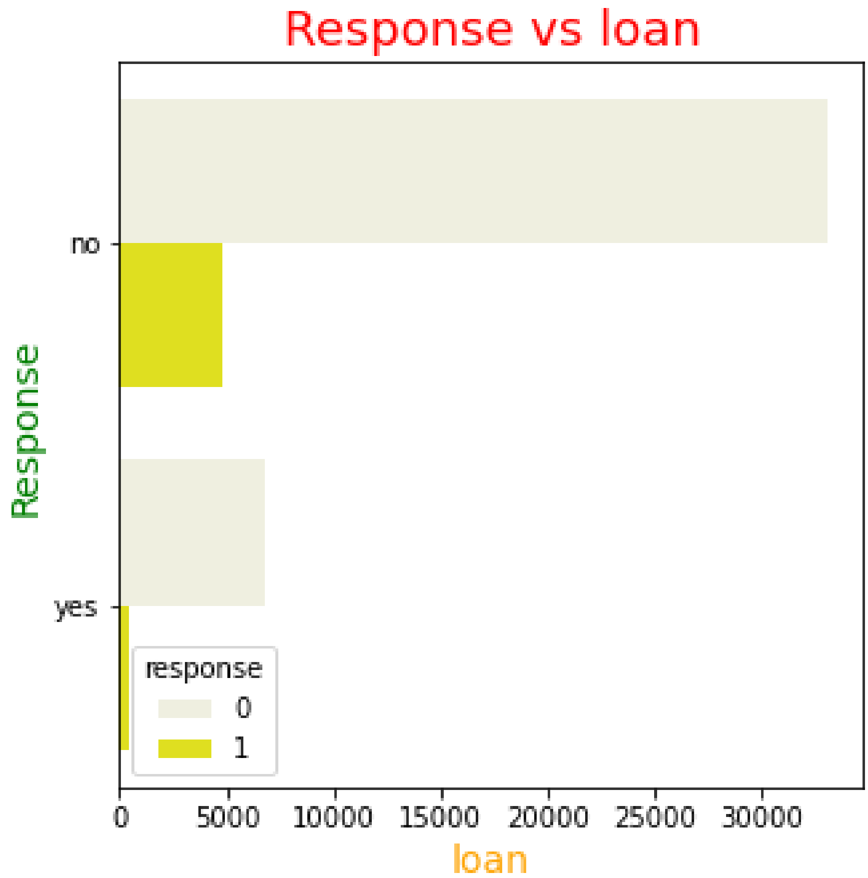

Response vs education
tertiary
secondary
unknown
primary
response
0
1
0
2500
5000
7500
10000
12500
15000
17500
20000
education
Response


Response vs targeted
yes
no
Response
response
0
1
0
5000
10000
15000
20000
25000
30000
targeted

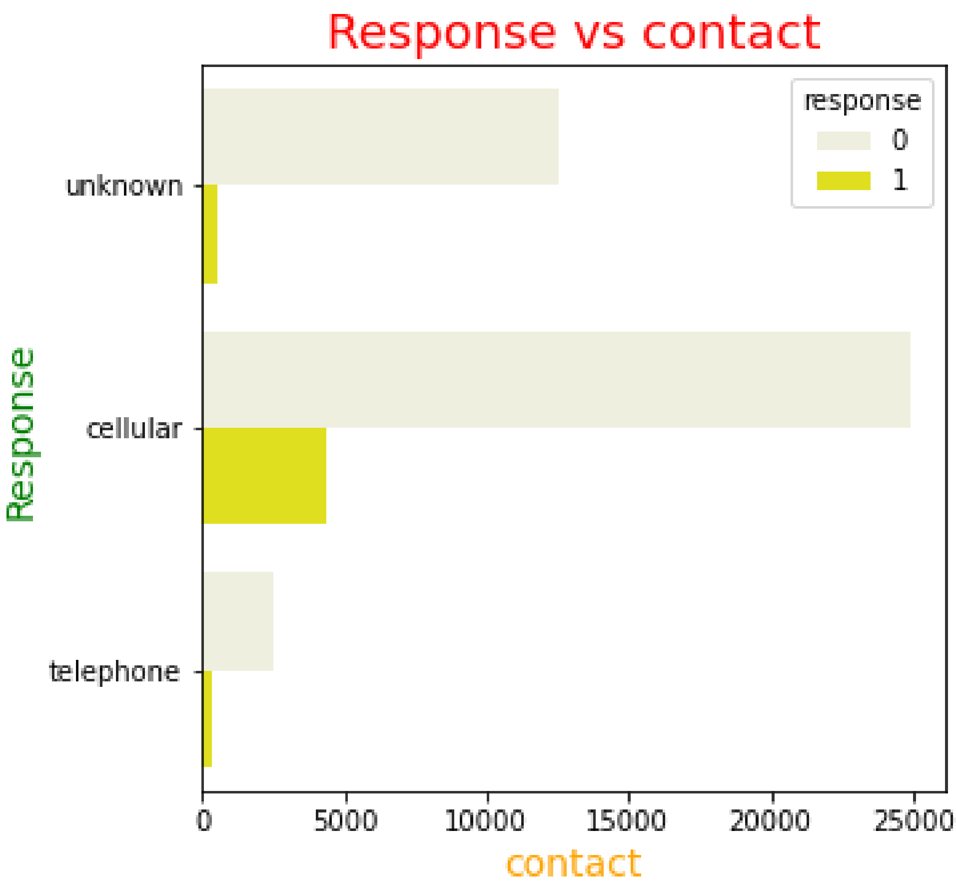

Response vs default
no
yes
Response
response
0
1
0
5000
10000
15000
20000
25000
30000
35000
40000
default

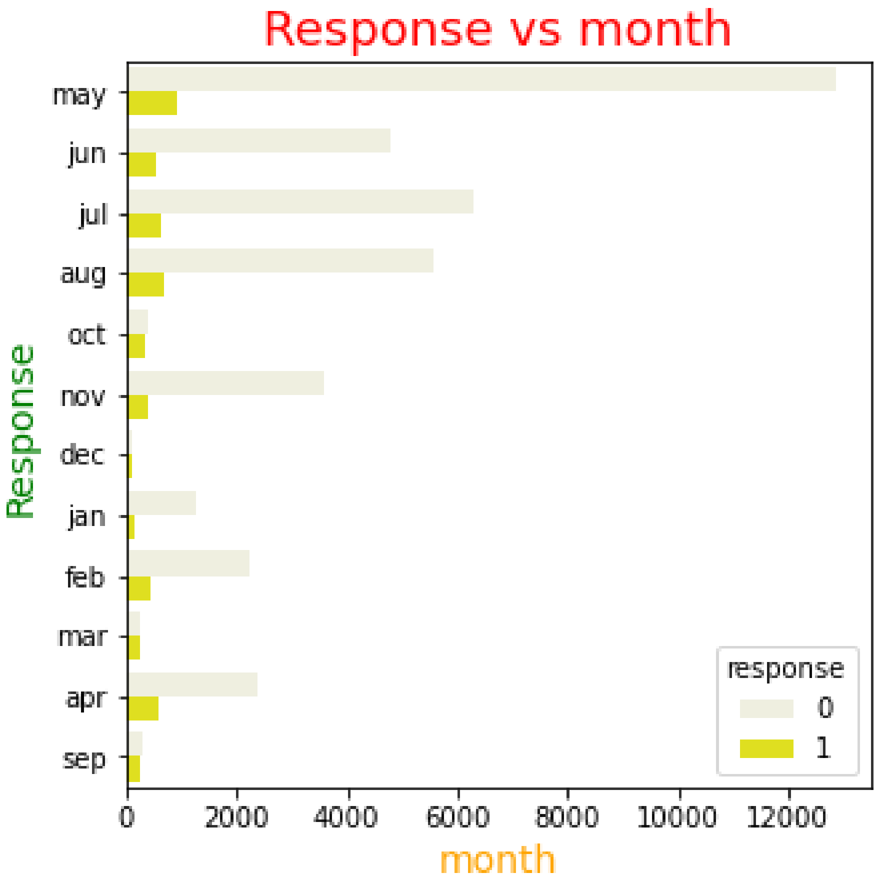


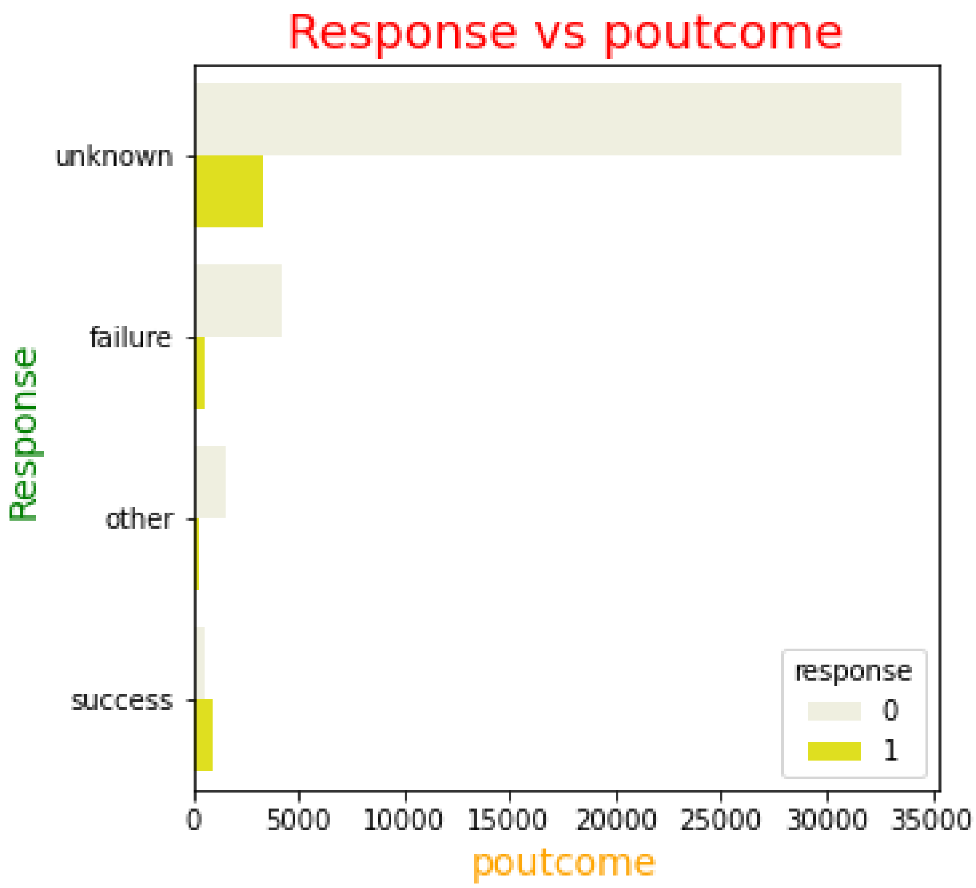
Response vs housing
yes
no
Response
response
0
1
0
5000
10000
15000
20000
housing



Response vs loan
no
yes
Response
response
0
1
0
5000
10000
15000
20000
25000
30000
loan


Response vs contact
response
0
1
unknown
cellular
telephone
Response
0
5000
10000
15000
20000
25000
contact


Response vs month
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
Response
response
0
1
0
2000
4000
6000
8000
10000
12000
month



'poutcome' column is not assosciated with target column because it has more missing values.

In [33]:

```
bk_df.drop('poutcome',axis=1,inplace=True)
```

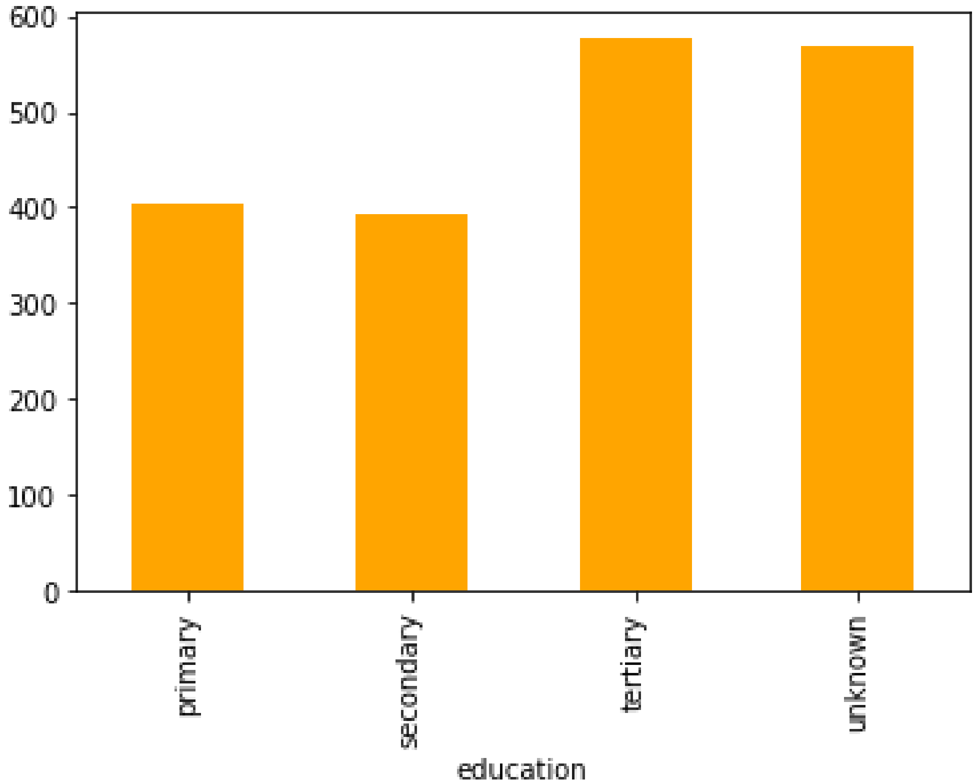
- Plot a horizontal bar graph with the median values of balance for each education level value. Which group has the highest median?

In [34]:

```
bk_df.groupby('education')['balance'].median().plot.bar(color='orange')
```

Out[34]:

```
<AxesSubplot:xlabel='education'>
```



Numerical Features

In [35]:

```
for col in num_col[1:]:
    print(col,bk_df[col].nunique())
```

```
salary 11
balance 7168
day 31
duration 1573
campaign 48
pdays 559
previous 41
response 2
```

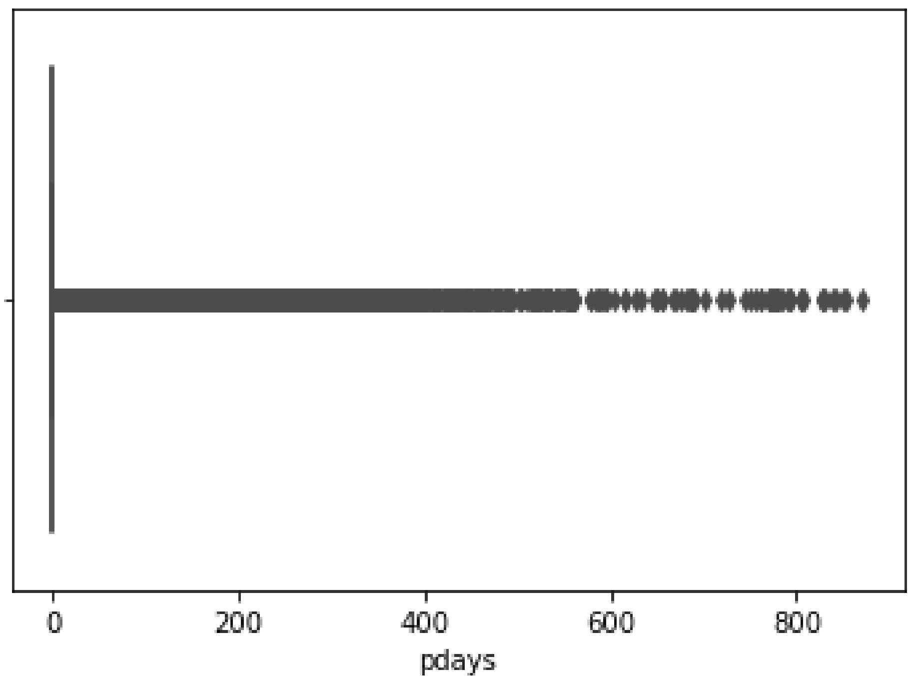
Make a box plot for pdays. Do you see any outliers?

In [36]:

```
sns.boxplot(bk_df['pdays'],color="blue")
```

Out[36]:

```
<AxesSubplot:xlabel='pdays'>
```



No.of outliers are observed in pdays coloumn

In [37]:

```
bk_df.corr()
```

Out[37]:

	age	salary	balance	day	duration	campaign	pdays	previous	response
age	1.000000	0.024357	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288	0.025155
salary	0.024357	1.000000	0.055469	0.027864	-0.009937	0.015005	-0.014968	0.014564	0.020012
balance	0.097783	0.055469	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674	0.052838
day	-0.009120	0.027864	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710	-0.028348
duration	-0.004648	-0.009937	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203	0.394521

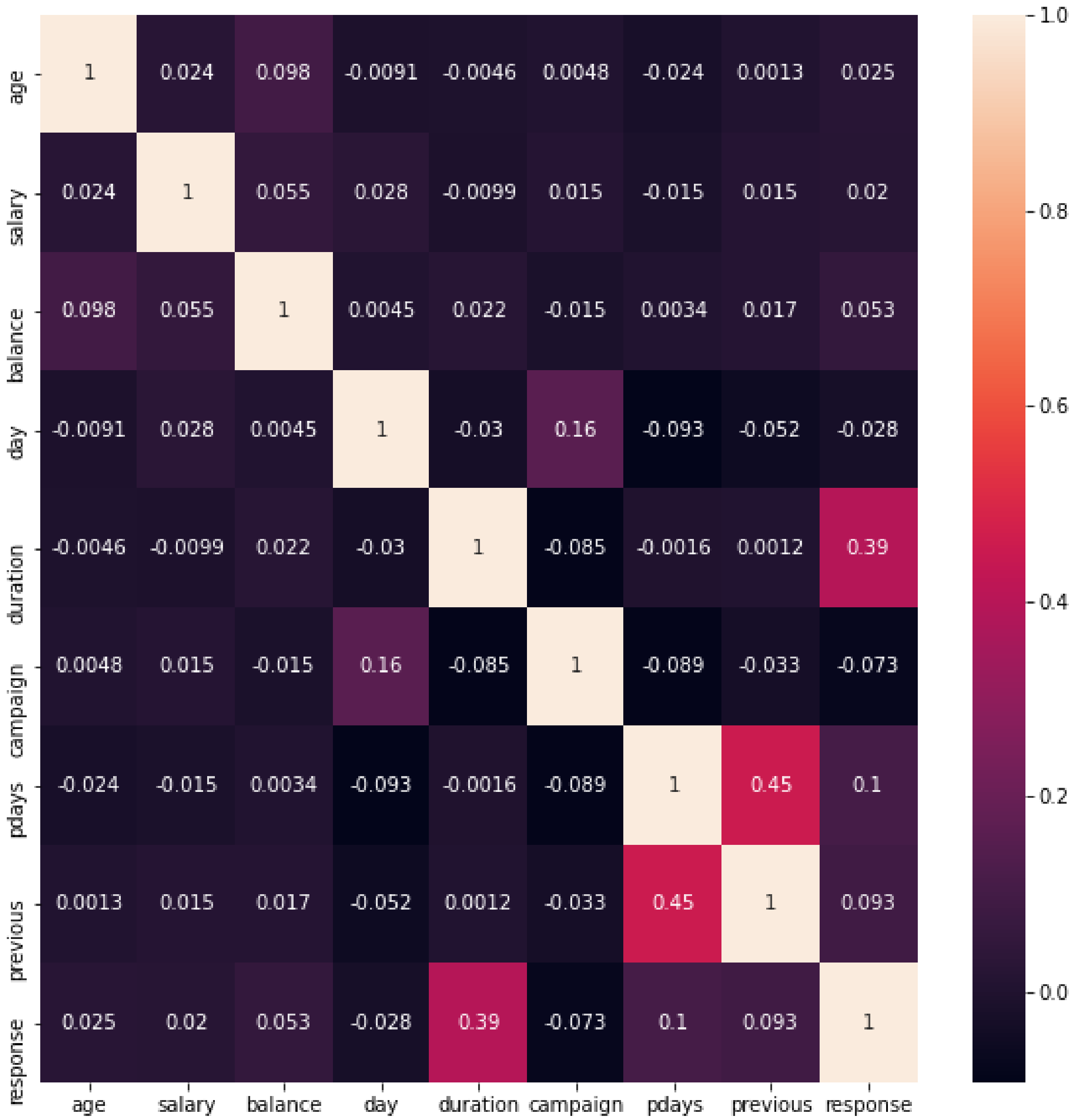
	age	salary	balance	day	duration	campaign	pdays	previous	response
campaign	0.004760	0.015005	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855	-0.073172
pdays	-0.023758	-0.014968	0.003435	-0.093044	-0.001565	-0.088628	1.000000	0.454820	0.103621
previous	0.001288	0.014564	0.016674	-0.051710	0.001203	-0.032855	0.454820	1.000000	0.093236
response	0.025155	0.020012	0.052838	-0.028348	0.394521	-0.073172	0.103621	0.093236	1.000000

In [40]:

```
plt.figure(figsize=(10,10))
sns.heatmap(bk_df.corr(),annot=True)
```

Out[40]:

```
<AxesSubplot:>
```

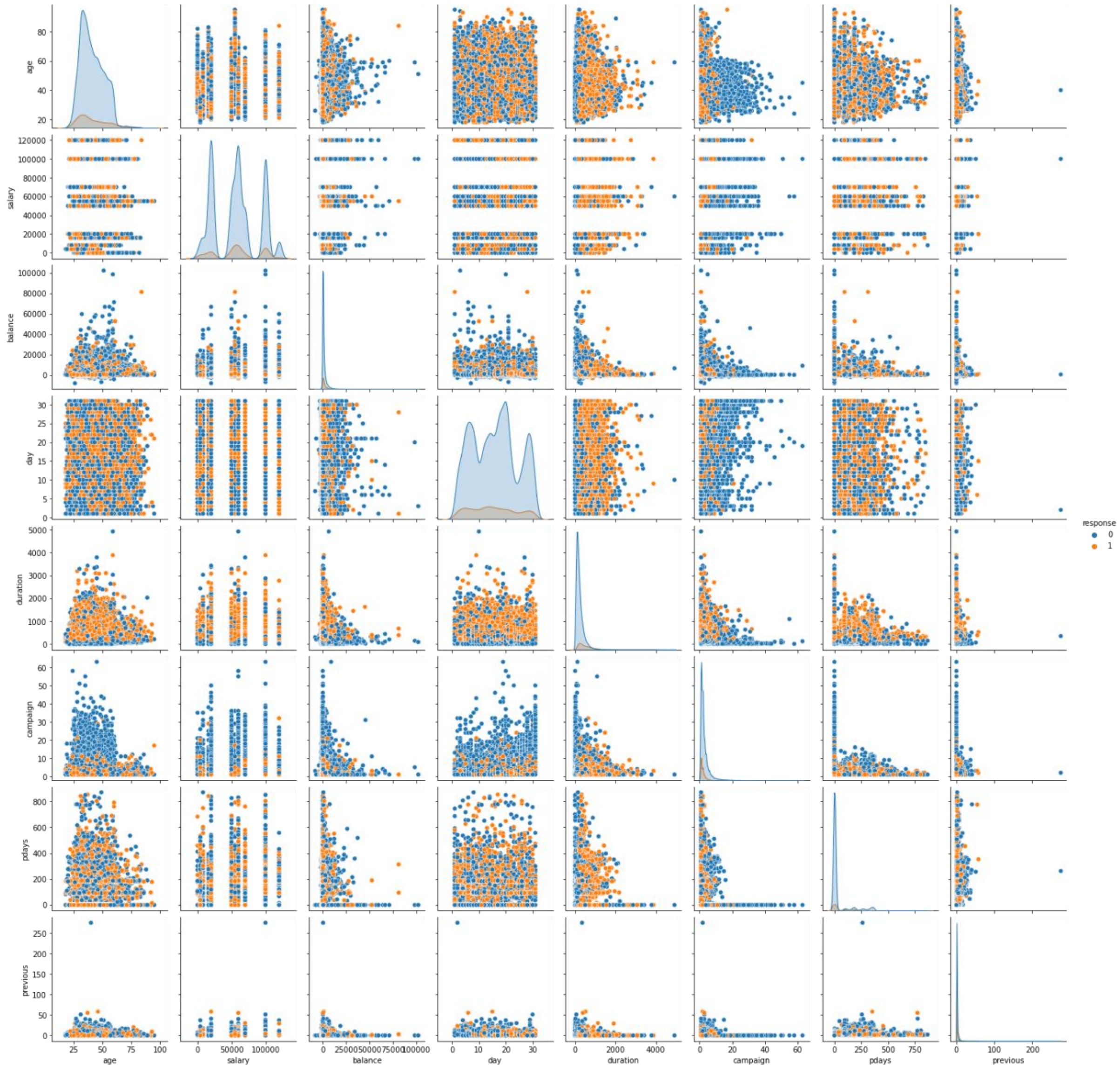


In [41]:

```
sns.pairplot(bk_df,hue='response')
```

Out[41]:

```
<seaborn.axisgrid.PairGrid at 0x26b4ec78640>
```



In [42]:

bk_df.info()

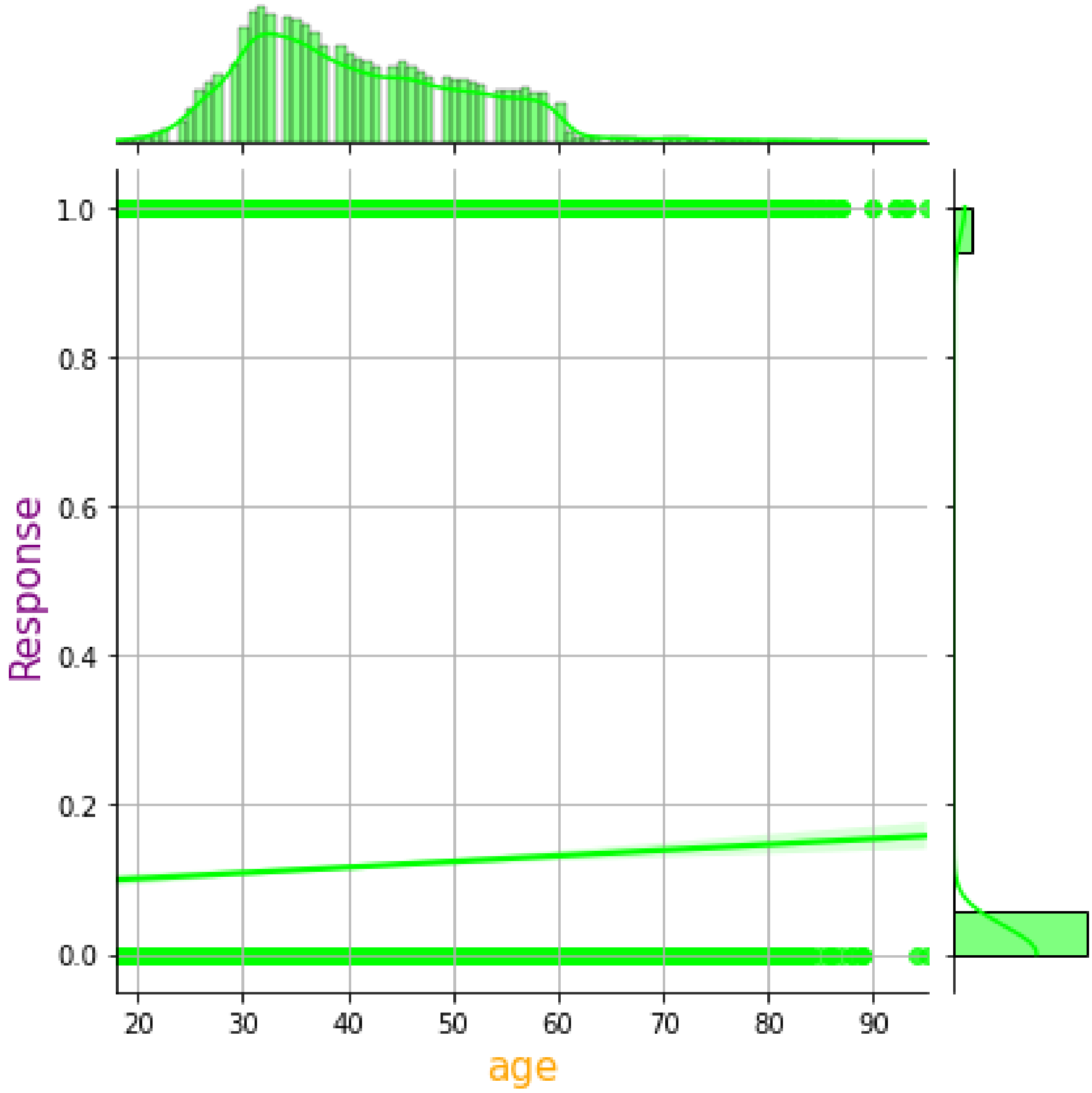
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 18 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   salary     45211 non-null  int64
 3   marital    45211 non-null  object
 4   education  45211 non-null  object
 5   targeted   45211 non-null  object
```

```
 6   default    45211 non-null  object
 7   balance    45211 non-null  int64
 8   housing    45211 non-null  object
 9   loan       45211 non-null  object
 10  contact    45211 non-null  object
 11  day        45211 non-null  int64
 12  month      45211 non-null  object
 13  duration   45211 non-null  int64
 14  campaign   45211 non-null  int64
 15  pdays      45211 non-null  int64
 16  previous   45211 non-null  int64
 17  response   45211 non-null  int64
dtypes: int64(9), object(9)
memory usage: 6.2+ MB
```

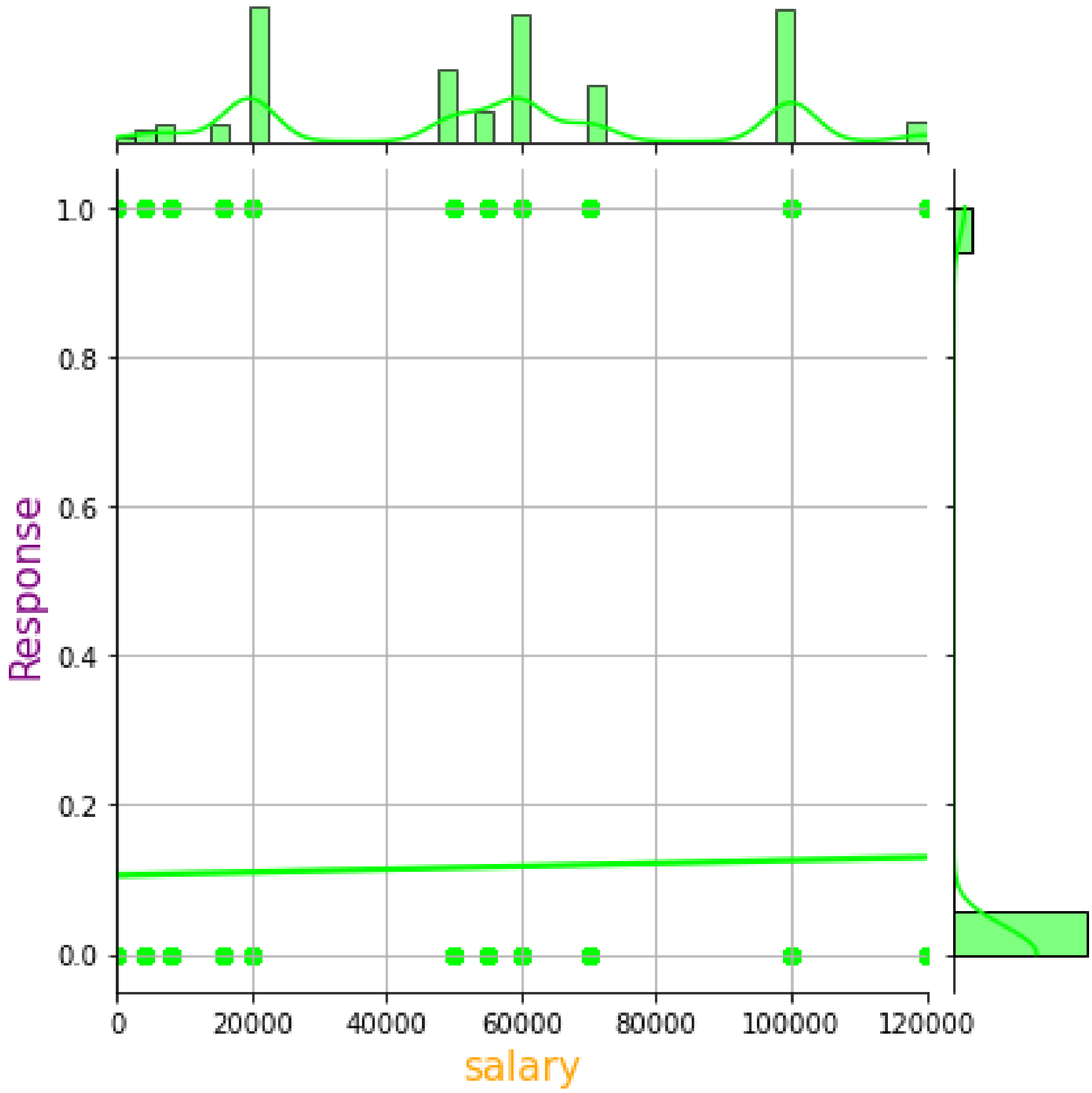
In [45]:

```python
for col in num_col[:-1]:
    plt.figure(figsize=(1,2))
    sns.jointplot(x = bk_df[col],y = bk_df["response"],kind='reg',color="lime")
    plt.xlabel(col,fontsize = 15,color="orange")
    plt.ylabel("Response",fontsize = 15,color="purple")
    plt.grid()
    plt.show()
```

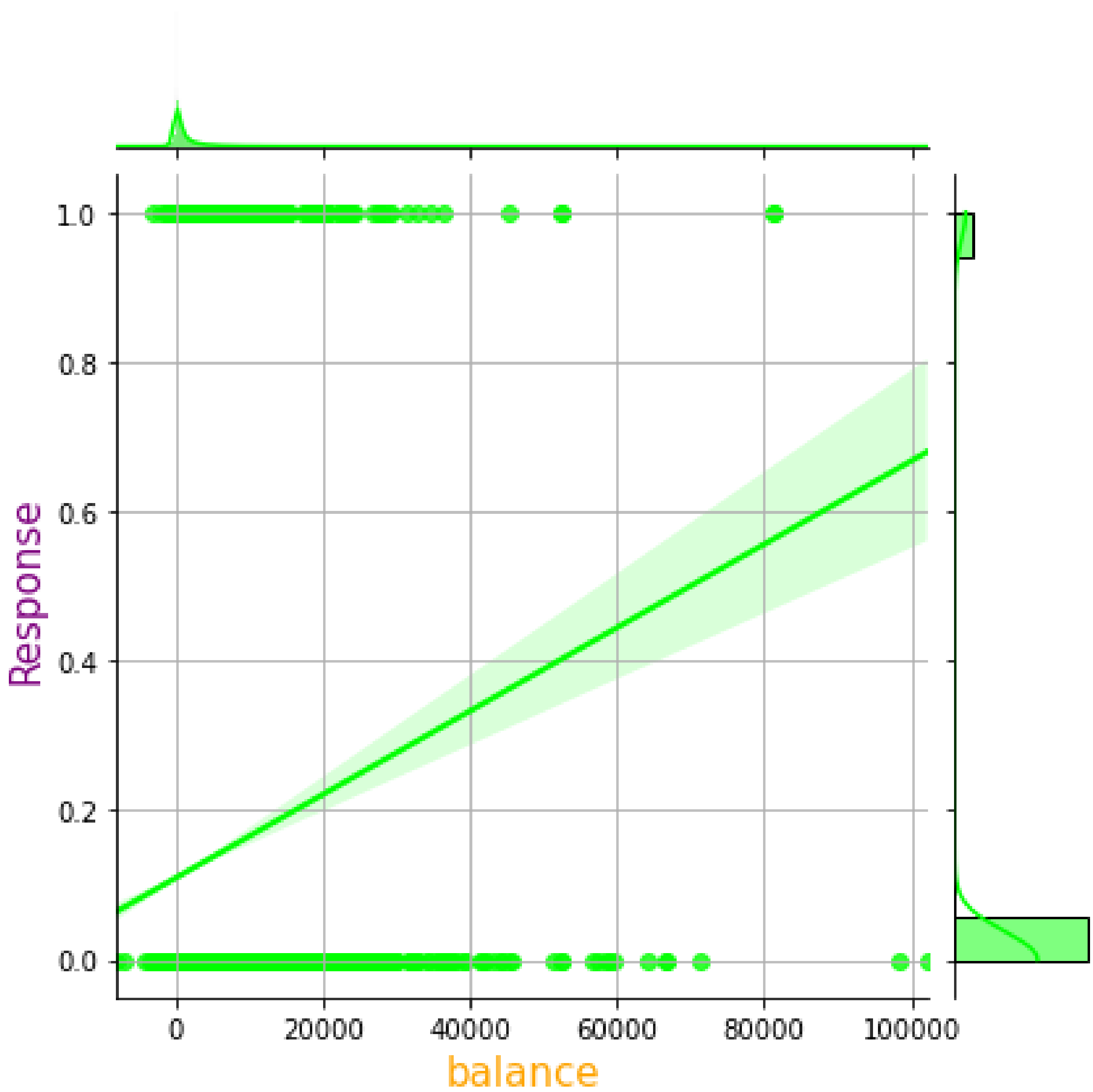
```
<Figure size 72x144 with 0 Axes>
```



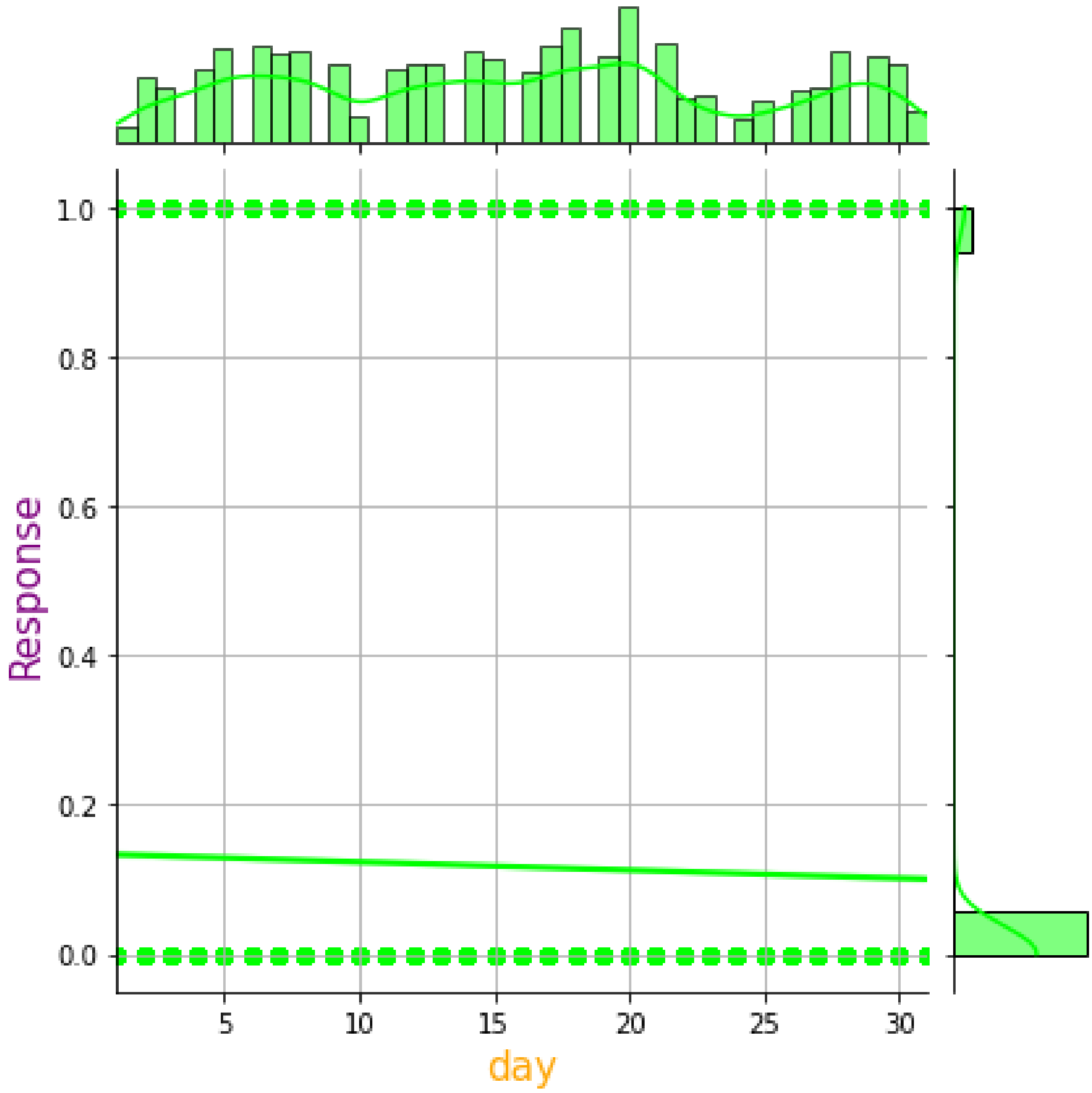
<Figure size 72x144 with 0 Axes>



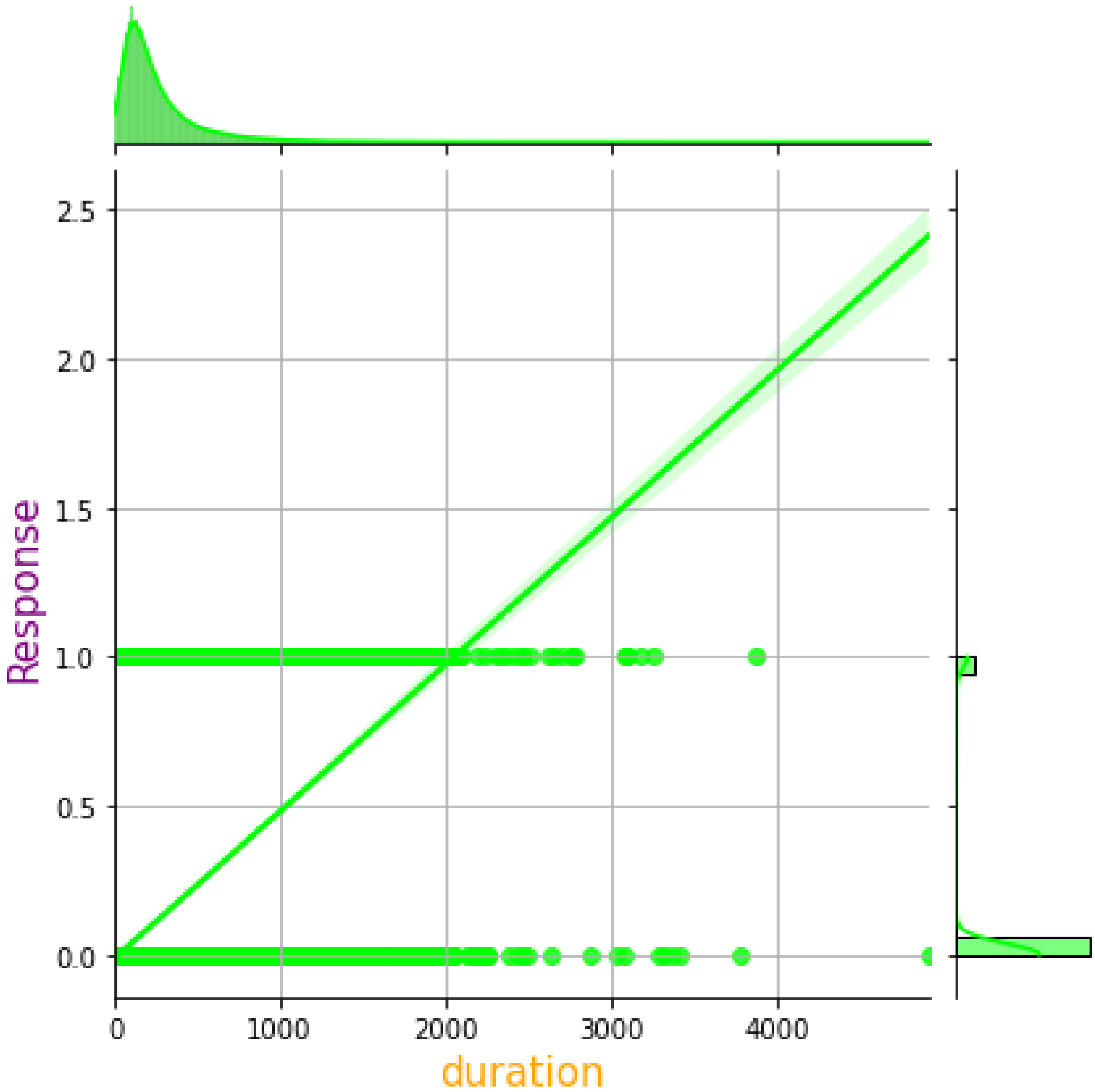
<Figure size 72x144 with 0 Axes>



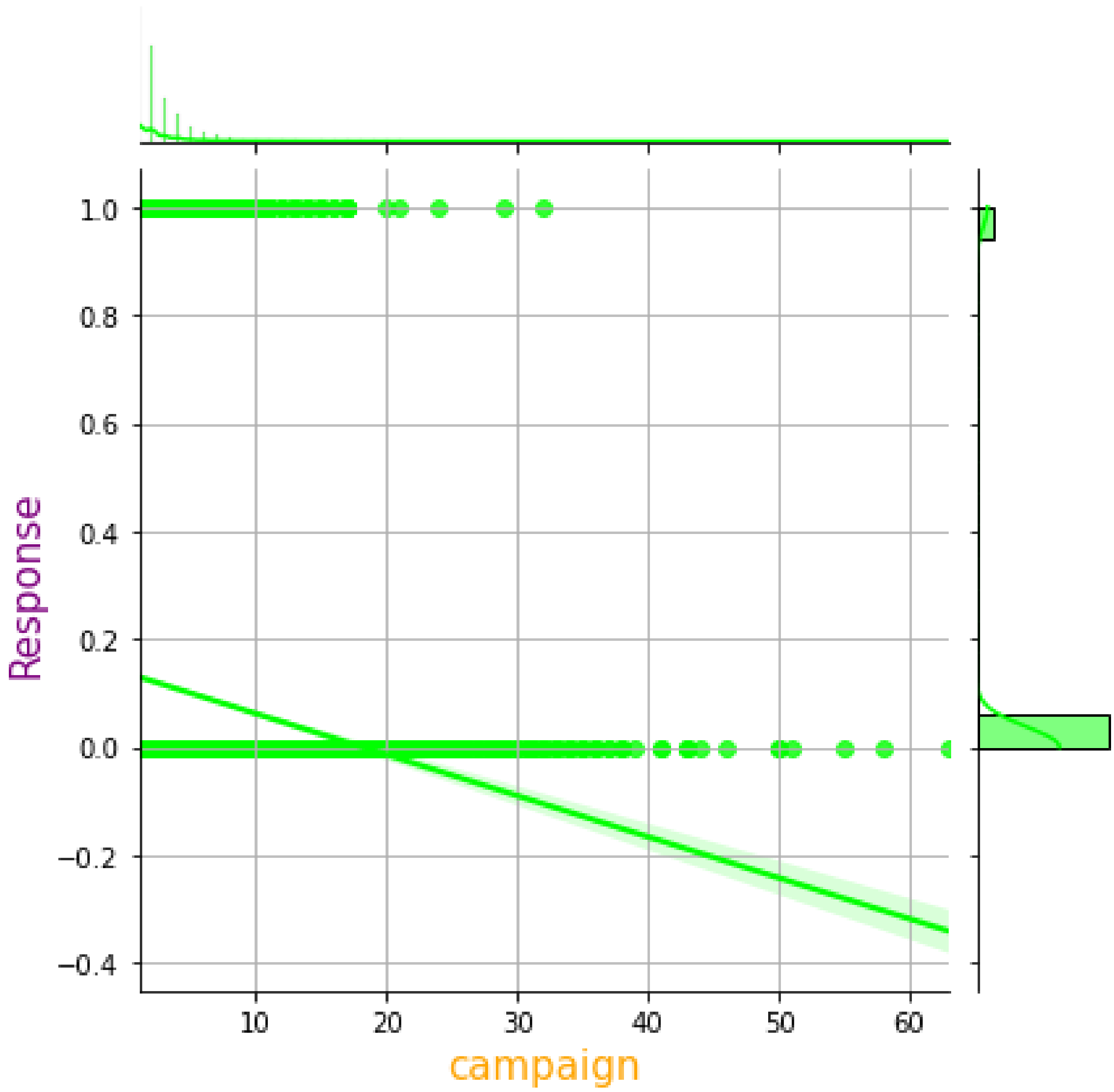
<Figure size 72x144 with 0 Axes>



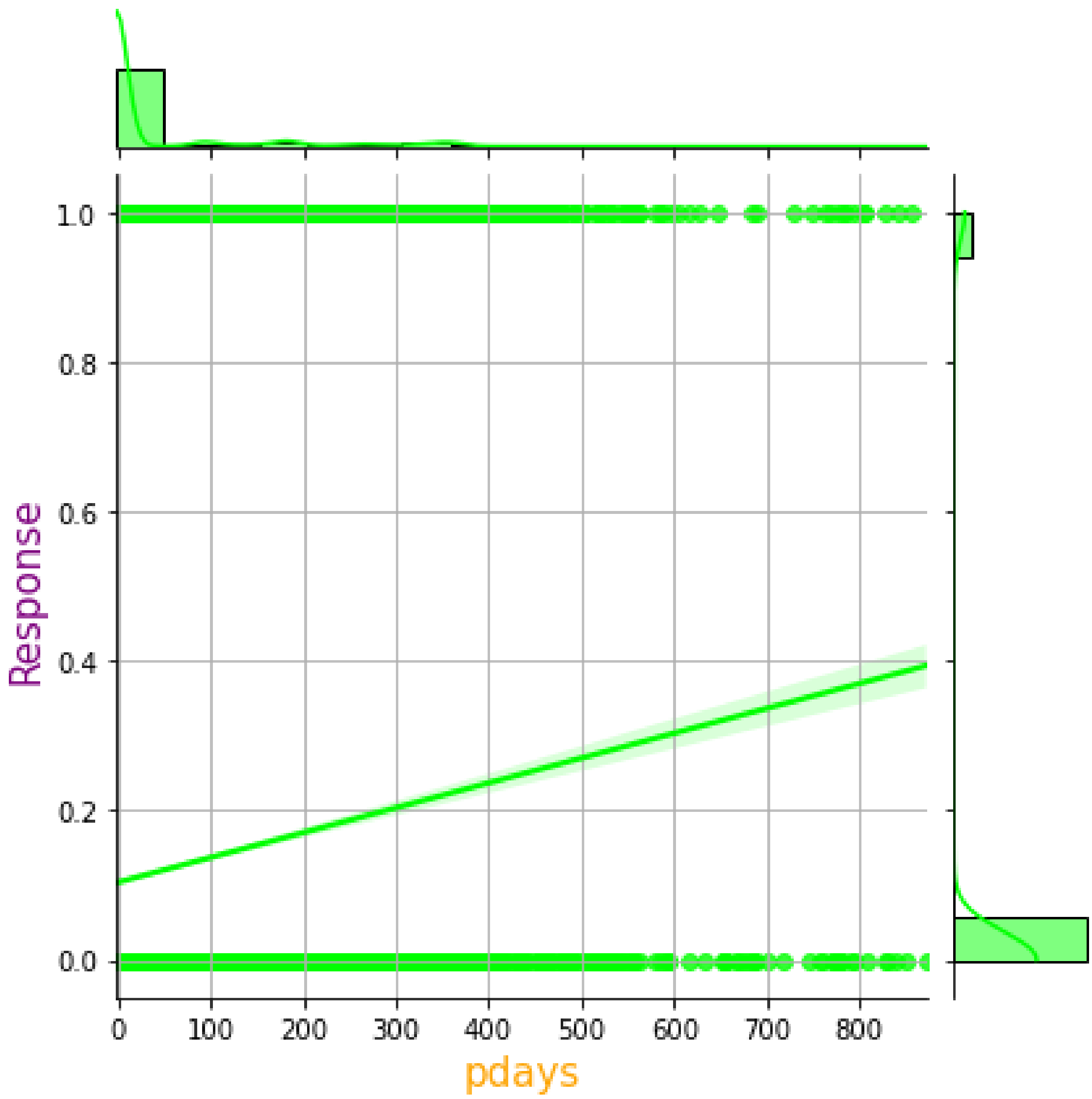
<Figure size 72x144 with 0 Axes>



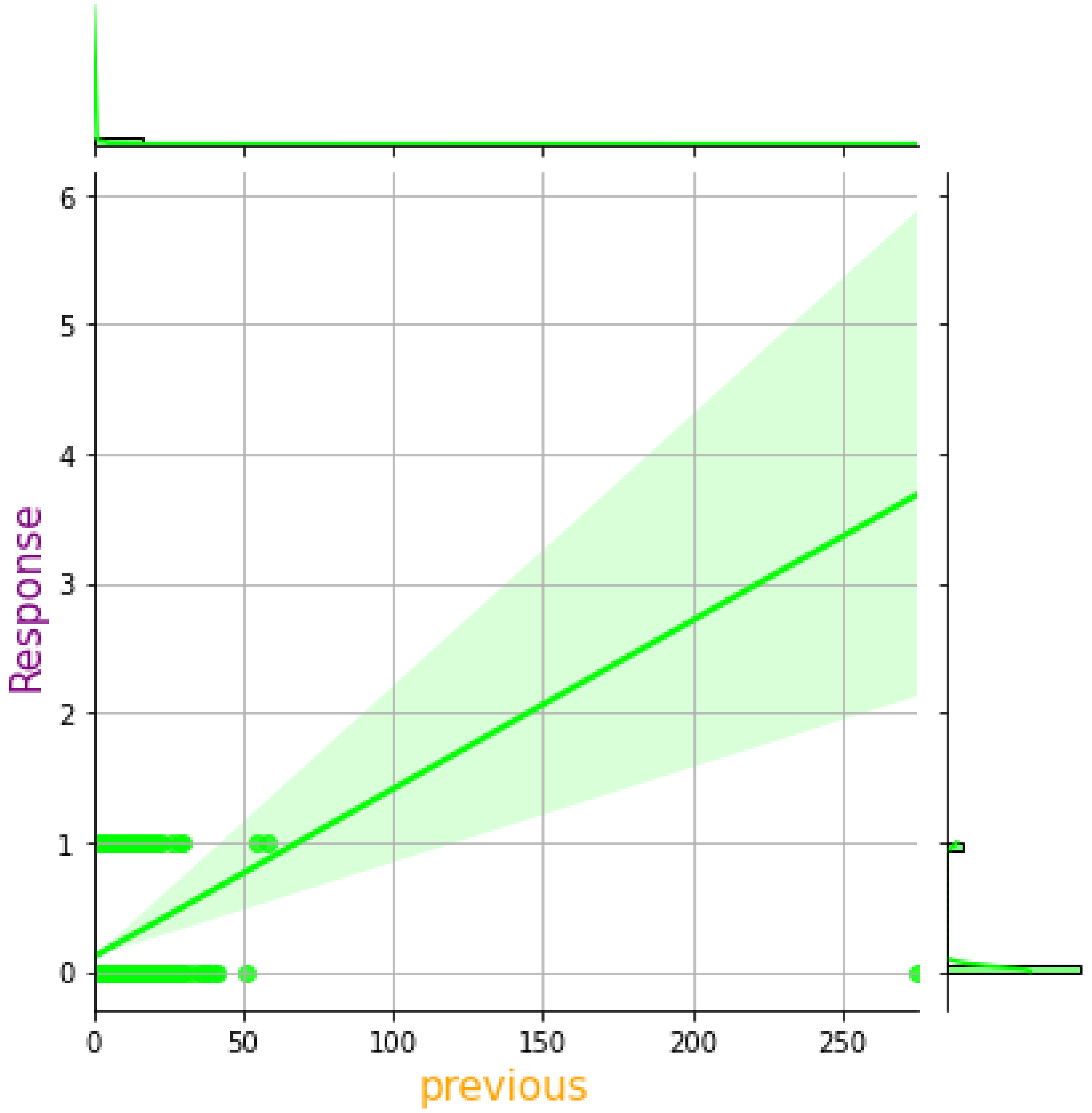
<Figure size 72x144 with 0 Axes>



<Figure size 72x144 with 0 Axes>



<Figure size 72x144 with 0 Axes>



-Are the features about the previous campaign data useful?

In [46]:

```
bk_df[['previous','response']].groupby("response").mean()
```

Out[46]:

	previous
response	
0	0.502154
1	1.170354

In [47]:

```
bk_df[['campaign','response']].groupby("response").mean()
```

Out[47]:

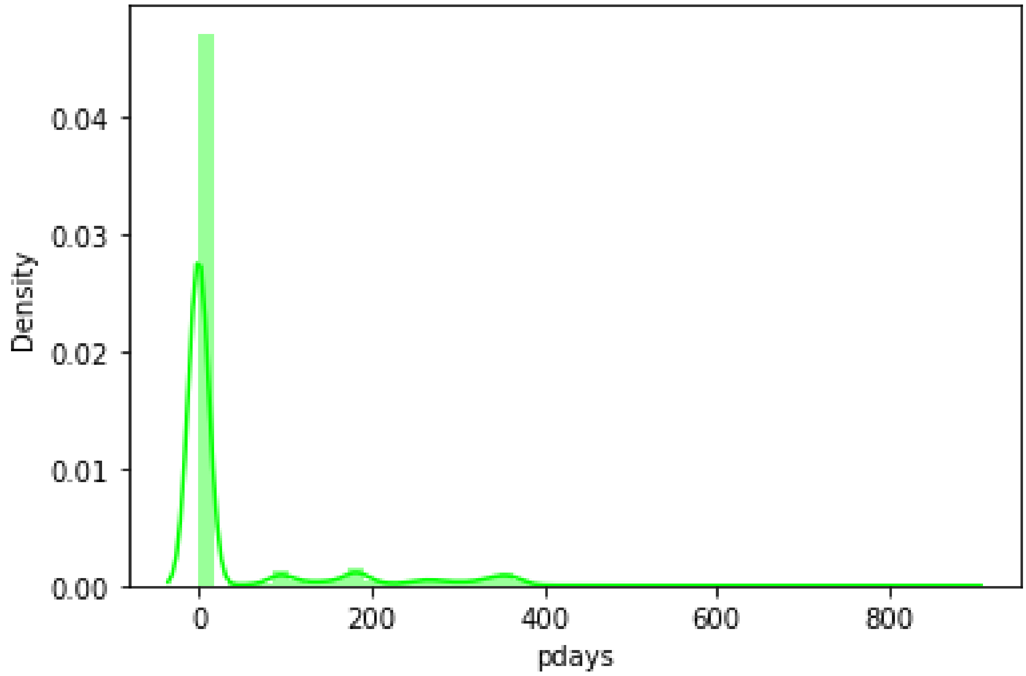
	campaign
response	
0	2.846350
1	2.141047

In [48]:

```
sns.distplot(bk_df['pdays'],color="lime")
```

Out[48]:

<AxesSubplot:xlabel='pdays', ylabel='Density'>



-how do you handle the pdays column with a value of -1 where the previous campaign data is missing?

In [49]:

```
bk_df['pdays_no_contact'] = np.where(bk_df['pdays']==-1,1,0)
bk_df['pdays_no_contact'].value_counts()
```

Out[49]:

```
1    36954
0     8257
Name: pdays_no_contact, dtype: int64
```

In [50]:

```
bk_df[['targeted','response']].groupby("targeted").mean()
```

Out[50]:

	response
targeted	
no	0.164409
yes	0.106603

In [51]:

```
bk_df[['housing','response']].groupby("housing").mean()
```

Out[51]:

	response
housing	
no	0.167024
yes	0.077000

In [52]:

```
bk_df[['default','response']].groupby("default").mean()
```

Out[52]:

default	response
no	0.117961
yes	0.063804

In [53]:

```
bk_df[['loan','response']].groupby("loan").mean()
```

Out[53]:

loan	response
no	0.126557
yes	0.066814

In [54]:

```
bk_df[['marital','response']].groupby("marital").mean()
```

Out[54]:

marital	response
divorced	0.119455

	response
marital	
married	0.101235
single	0.149492

In [55]:

```
bk_df[['education','response']].groupby("education").mean()
```

Out[55]:

	response
education	
primary	0.086265
secondary	0.105594
tertiary	0.150064
unknown	0.135703

In [56]:

```
bk_df[['job','response']].groupby("job").mean()
```

Out[56]:

	response
job	
admin.	0.122027
blue-collar	0.072750

	response
job	
entrepreneur	0.082717
housemaid	0.087903
management	0.137556
retired	0.227915
self-employed	0.118429
services	0.088830
student	0.286780
technician	0.110570
unemployed	0.155027
unknown	0.118056

In [57]:

```
bk_df['month'].unique()
```

Out[57]:

```
array(['may', 'jun', 'jul', 'aug', 'oct', 'nov', 'dec', 'jan', 'feb',
       'mar', 'apr', 'sep'], dtype=object)
```

In [58]:

```
dict={'jan':1,'feb':2,'mar':3,'apr':4,'may':5,'jun':6,'jul':7,'aug':8,'sep':9,'oct':10,'nov':11,'dec':12}
bk_df['month']=bk_df['month'].map(dict)
```

In [59]:

```
bk_df['month'].unique()
```

Out[59]:

```
array([ 5,  6,  7,  8, 10, 11, 12,  1,  2,  3,  4,  9], dtype=int64)
```

In [60]:

```
bk_df.head()
```

Out[60]:

	age	job	salary	marital	education	targeted	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	response	pdays_no_contact
0	58	management	100000	married	tertiary	yes	no	2143	yes	no	unknown	5	5	261	1	-1	0	0	1
1	44	technician	60000	single	secondary	yes	no	29	yes	no	unknown	5	5	151	1	-1	0	0	1
2	33	entrepreneur	120000	married	secondary	yes	no	2	yes	yes	unknown	5	5	76	1	-1	0	0	1
3	47	blue-collar	20000	married	unknown	no	no	1506	yes	no	unknown	5	5	92	1	-1	0	0	1
4	33	unknown	0	single	unknown	no	no	1	no	no	unknown	5	5	198	1	-1	0	0	1

In [61]:

cat_col

Out[61]:

```
['job',
 'marital',
 'education',
 'targeted',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'poutcome']
```

Data Preprocessing

In [62]:

```python
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import MinMaxScaler

cat_features = ['job','marital','education','targeted','default','housing','loan','contact','month']

X = pd.get_dummies( bk_df, columns=cat_features, drop_first=True)
```

In [64]:

```python
sc= MinMaxScaler()
a = sc.fit_transform(bk_df[['salary']])
b = sc.fit_transform(bk_df[['balance']])
c = sc.fit_transform(bk_df[['day']])
d = sc.fit_transform(bk_df[['duration']])
e = sc.fit_transform(bk_df[['campaign']])
f = sc.fit_transform(bk_df[['pdays']])
g = sc.fit_transform(bk_df[['previous']])
h = sc.fit_transform(bk_df[['pdays_no_contact']])
```

In [65]:

```python
X['salary'] = a
X['balance'] = b
```

```
X['day']=c
X['duration']=d
X['campaign']=e
X['pdays'] = f
X['previous'] = g
X['pdays_no_contact']=h
```

In [66]:

```
X.shape
```

Out[66]:

```
(45211, 43)
```

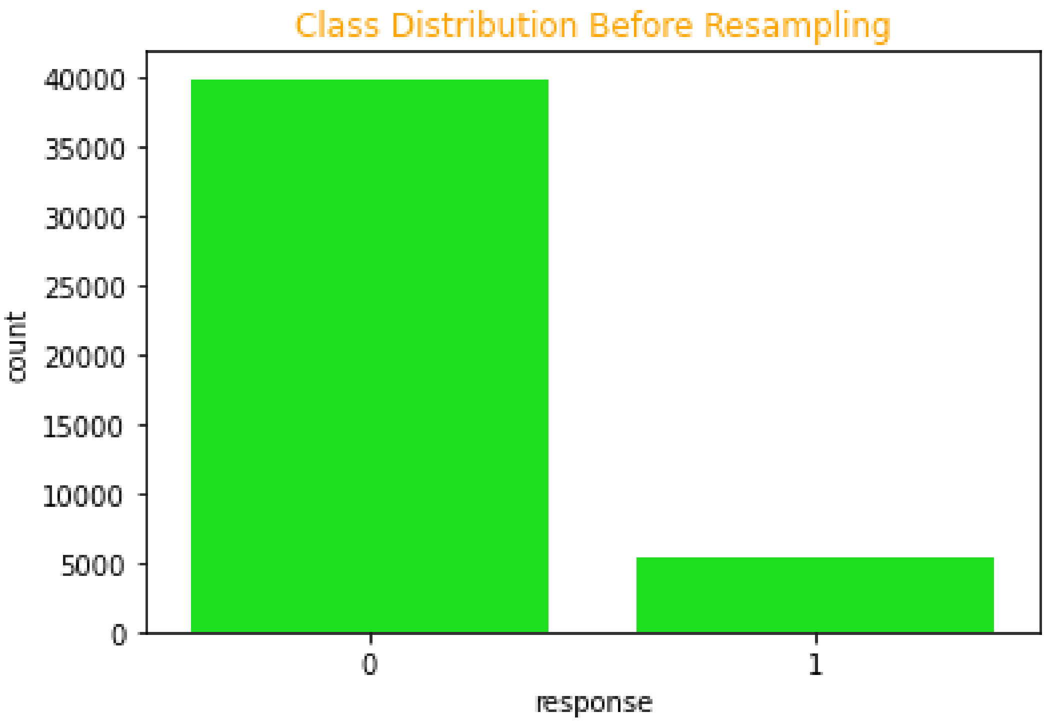
Resampling

In [78]:

```
sns.countplot('response', data=bk_df,color="lime").set_title('Class Distribution Before Resampling',color="orange")
```

Out[78]:

```
Text(0.5, 1.0, 'Class Distribution Before Resampling')
```



In [79]:

```
X_no = X[X.response == 0]
X_yes = X[X.response == 1]
```

In [80]:

```
X_yes_upsampled = X_yes.sample(n=len(X_no), replace=True, random_state=42)
print(len(X_yes_upsampled))
```

```
39922
```

In [81]:

```
X_upsampled = X_no.append(X_yes_upsampled).reset_index(drop=True)
print(len(X_upsampled))
```

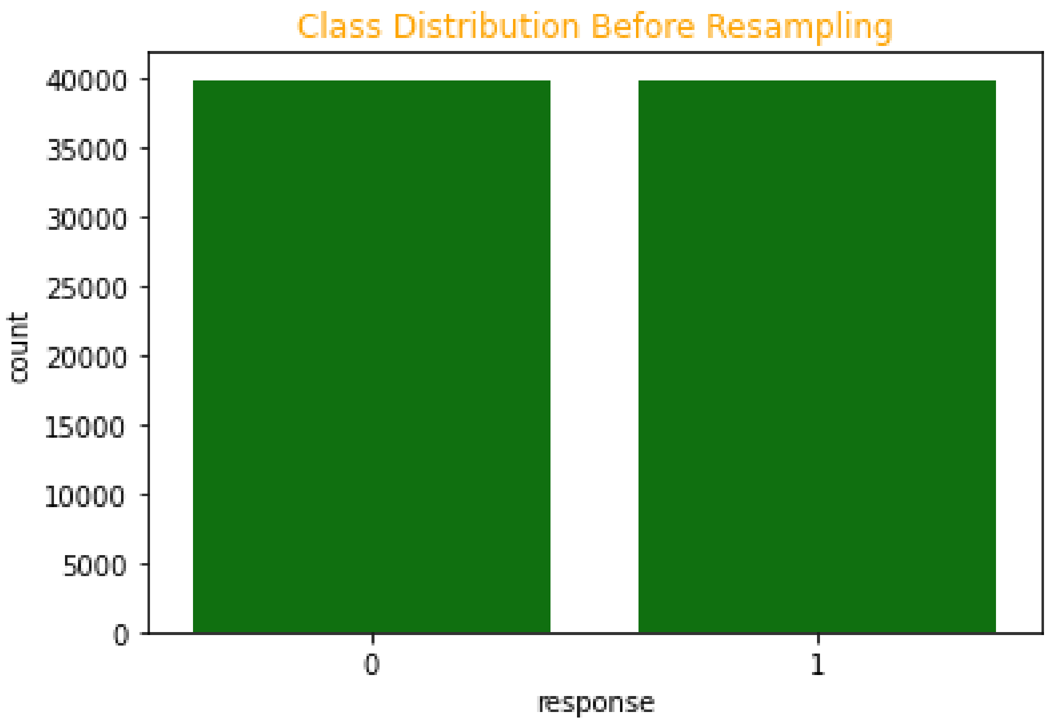
```
79844
```

In [83]:

```
sns.countplot('response', data=X_upsampled,color="green").set_title('Class Distribution Before Resampling',color="orange")
```

Out[83]:

```
Text(0.5, 1.0, 'Class Distribution Before Resampling')
```



ML model

Train Test and split

Now it's time to do a train test split, and train our model!

In [84]:

```
from sklearn.model_selection import train_test_split
```

In [85]:

```
x = X_upsampled.drop(['response'], axis=1)  #features (independent variables)
y = X_upsampled['response']             #target (dependent variable)
```

In [86]:

```
X_train, X_test, Y_train, Y_test = train_test_split(x,y, test_size=0.25,random_state=70)
```

Logistic Regression

In [87]:

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()

lr.fit(X_train,Y_train)
```

Out[87]:

```
LogisticRegression()
```

In [88]:

```
lr_pred=lr.predict(X_test)
```

In [89]:

```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [93]:

```
Y_test[:20]
```

Out[93]:

```
51853    1
27901    0
40500    1
38611    0
24872    0
19672    0
17011    0
77503    1
30667    0
64021    1
51223    1
61692    1
10909    0
65933    1
67435    1
```

```
72131    1
4244     0
14755    0
61867    1
5849     0
Name: response, dtype: int64
```

In [94]:

```
lr_pred[:20]
```

Out[94]:

```
array([1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0],
      dtype=int64)
```

In [95]:

```
confusion_matrix(Y_test,lr_pred)
```

Out[95]:

```
array([[8258, 1686],
       [1822, 8195]], dtype=int64)
```

In [96]:

```
accuracy_score(Y_test,lr_pred)*100
```

Out[96]:

```
82.42573017383899
```

In [97]:

```
print(classification_report(Y_test,lr_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.83      0.82      9944
           1       0.83      0.82      0.82     10017

    accuracy                           0.82     19961
   macro avg       0.82      0.82      0.82     19961
weighted avg       0.82      0.82      0.82     19961
```

Accuracy of model with logistic regression is 82%.

Random Forest

In [98]:

```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=100)

rfc.fit(X_train, Y_train)

rf_pred = rfc.predict(X_test)
```

In [99]:

```
Y_test[:20]
```

Out[99]:

```
51853    1
27901    0
40500    1
38611    0
24872    0
19672    0
17011    0
77503    1
30667    0
64021    1
51223    1
61692    1
10909    0
65933    1
67435    1
72131    1
4244     0
14755    0
61867    1
5849     0
Name: response, dtype: int64
```

In [100]:

```
rf_pred[:20]
```

Out[100]:

```
array([1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0],
      dtype=int64)
```

In [101]:

```
confusion_matrix(Y_test,rf_pred)
```

Out[101]:

```
array([[ 9286,   658],
       [   10, 10007]], dtype=int64)
```

In [102]:

```
accuracy_score(Y_test,rf_pred)*100
```

Out[102]:

```
96.65347427483593
```

In [103]:

```
print(classification_report(Y_test,rf_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.93      0.97      9944
           1       0.94      1.00      0.97     10017

    accuracy                           0.97     19961
   macro avg       0.97      0.97      0.97     19961
weighted avg       0.97      0.97      0.97     19961
```

Accuracy of model with Random forest is 97%

By comparing the models we get the highest accurcay percentage of 97% rather than Logistic regression algorithm model.