Importing neccessary packages

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
import numpy as np, pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import MinMaxScaler

from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_s
from sklearn.ensemble import RandomForestClassifier
import statsmodels.api as sm

from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
```

In [3]:

```
%matplotlib inline
```

Importing data-set

In [4]:

```
df = pd.read_csv('bank-marketing.csv')
df.head()
```

Out[4]:

	age	job	salary	marital	education	targeted	default	balance	hou
0	58	management	100000	married	tertiary	yes	no	2143	
1	44	technician	60000	single	secondary	yes	no	29	
2	33	entrepreneur	120000	married	secondary	yes	no	2	
3	47	blue-collar	20000	married	unknown	no	no	1506	
4	33	unknown	0	single	unknown	no	no	1	

Performing Basic EDA

In [5]:

```
# Dimensions of Data-frame

df.shape
```

Out[5]:

```
(45211, 19)
```

In [6]:

```
# Data types present in Data-frames

df.dtypes
```

Out[6]:

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

In [7]:

```
# Overview of the Type and missing values present in each column

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
```

> Data types are consistent and there are no missing values present, need to analyse 'unknown' categories.

EDA

In [8]:

```
# Finding the categories (levels) present in each column (categorical ones)

for i in df.select_dtypes('object').columns:
    print(i, '\n')
    print(df[i].value_counts(normalize = True) * 100)
    print('\n\n')
```

```
job 

blue-collar      21.525735
management       20.919688
technician       16.803433
admin.           11.437482
services          9.188029
retired           5.007631
self-employed     3.492513
entrepreneur      3.289023
unemployed        2.882042
housemaid         2.742695
student           2.074716
unknown           0.637013
Name: job, dtype: float64



marital 

married     60.193316
single      28.289576
divorced    11.517109
Name: marital, dtype: float64



education 

secondary    51.319369
tertiary     29.419831
primary      15.153392
unknown       4.107407
Name: education, dtype: float64



targeted 

yes    82.039769
no     17.960231
```

```
Name: targeted, dtype: float64


default

no     98.197341
yes     1.802659
Name: default, dtype: float64


housing

yes    55.583818
no     44.416182
Name: housing, dtype: float64


loan

no     83.977351
yes    16.022649
Name: loan, dtype: float64


contact

cellular     64.774059
unknown      28.798301
telephone     6.427639
Name: contact, dtype: float64


month

may    30.448342
jul    15.250713
aug    13.817434
jun    11.813497
nov     8.781049
apr     6.485147
feb     5.859194
jan     3.103227
oct     1.632346
sep     1.280662
mar     1.055053
```

```
dec      0.473336
Name: month, dtype: float64
```

```
poutcome

unknown    81.747805
failure    10.840282
other       4.069806
success     3.342107
Name: poutcome, dtype: float64
```

```
response

no     88.30152
yes    11.69848
Name: response, dtype: float64
```

> Since poutcome has more than >50% of data as unknown it can be ignored as it won't aid in our analysis

In [9]:

```python
# Checking dimension before dropping records

df.shape
```

Out[9]:

```
(45211, 19)
```

In [10]:

```python
df1 = df[~(df['pdays'] == -1)]
df1.shape
```

Out[10]:

```
(8257, 19)
```

In [11]:

```
# Basic statistics post-dropping records for pdays

df1['pdays'].describe()
```

Out[11]:

```
count    8257.000000
mean      224.577692
std       115.344035
min         1.000000
25%       133.000000
50%       194.000000
75%       327.000000
max       871.000000
Name: pdays, dtype: float64
```

In [12]:

```
# Confirming records were dropped

df.shape
```

Out[12]:

```
(45211, 19)
```

In [13]:

```
# Basic statistics post-dropping records

df.describe()
```

Out[13]:

	age	salary	balance	day	duration
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	57006.171065	1362.272058	15.806419	258.163080
std	10.618762	32085.718415	3044.765829	8.322476	257.527812
min	18.000000	0.000000	-8019.000000	1.000000	0.000000
25%	33.000000	20000.000000	72.000000	8.000000	103.000000
50%	39.000000	60000.000000	448.000000	16.000000	180.000000
75%	48.000000	70000.000000	1428.000000	21.000000	319.000000
max	95.000000	120000.000000	102127.000000	31.000000	4918.000000

- balance Negative
- pdays: -1 means not contacted

> Also, 75% of data is -1 so practically a useless column

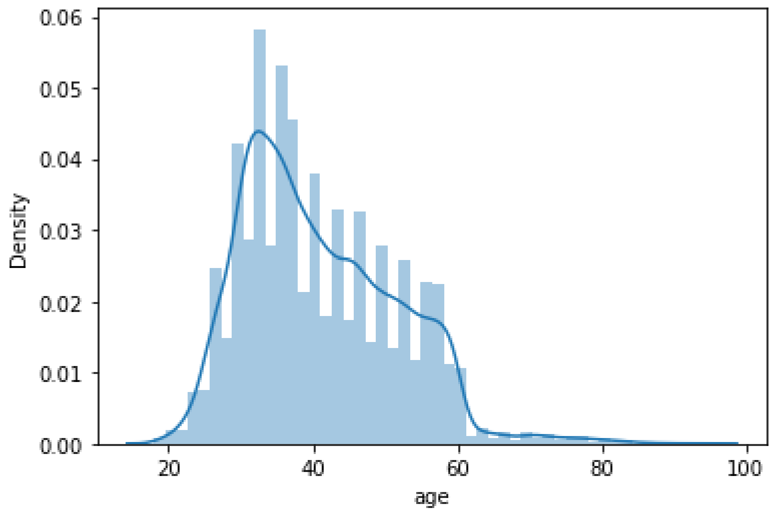
Visualization

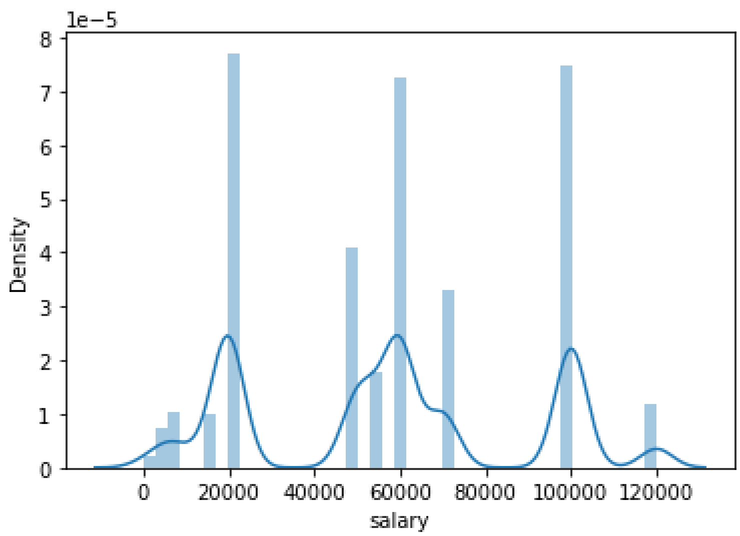
Uni-variant analysis

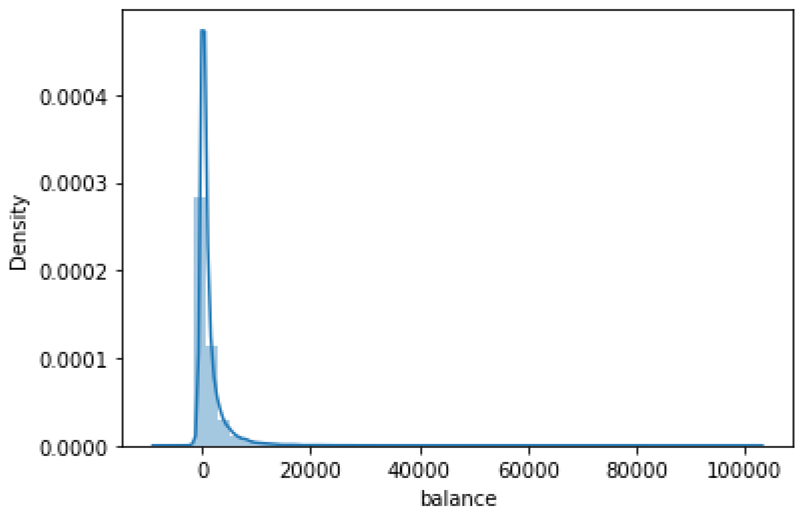
Disribution of Numeric columns

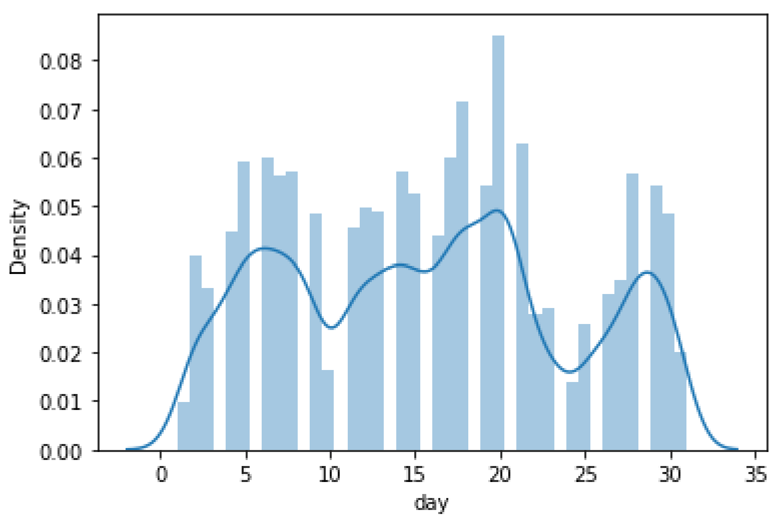
In [14]:

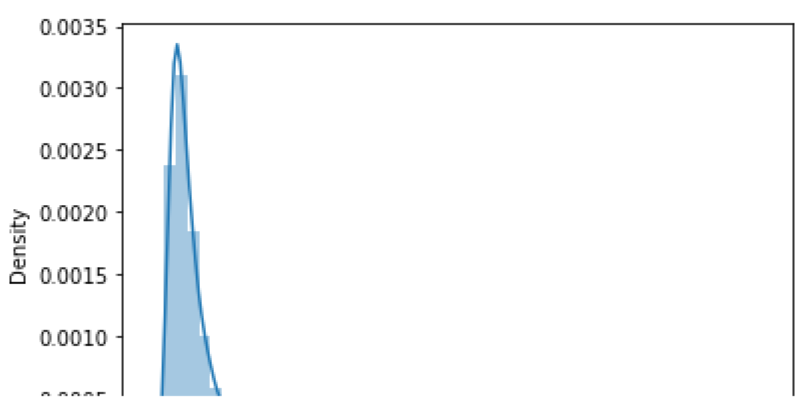
```
# Checking distribution for numeric columns

for i in df.select_dtypes('number'):
    sns.distplot(df[i])
    plt.show()
```

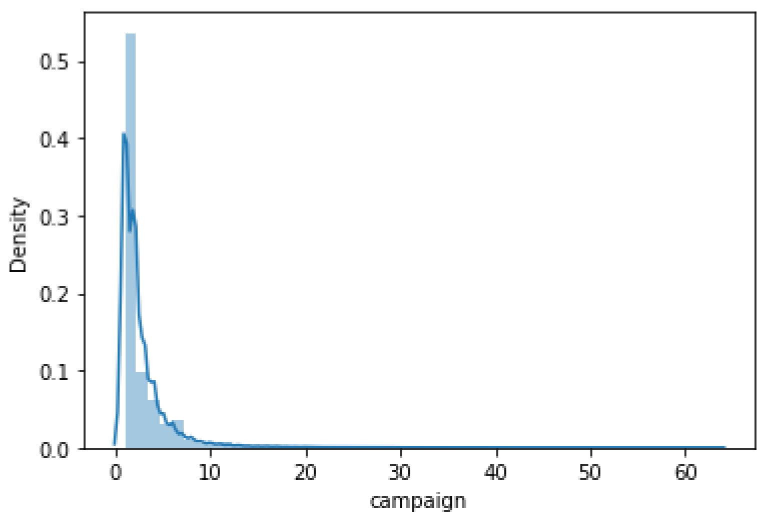


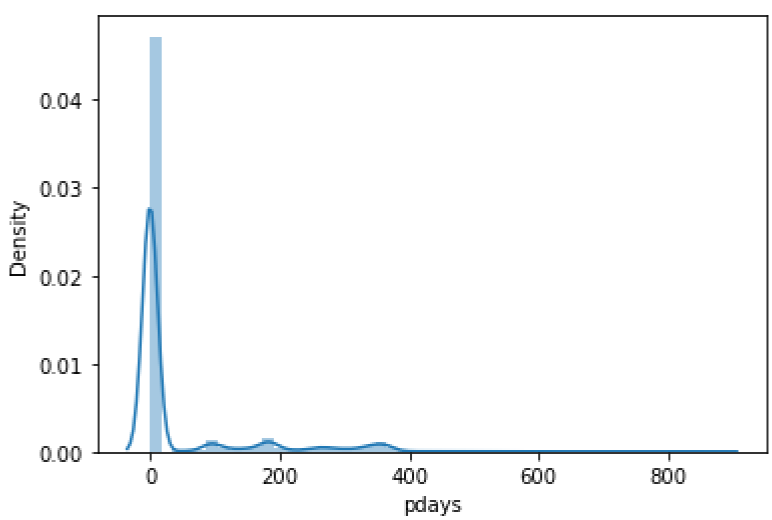


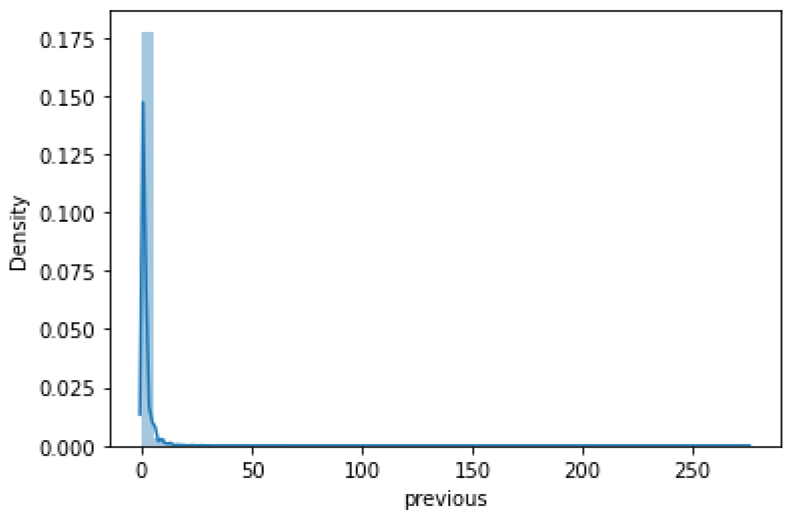

Density
0.0004
0.0003
0.0002
0.0001
0.0000
0
20000
40000
60000
80000
100000
balance


Density
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
5
10
15
20
25
30
35
day


0.0035
0.0030
0.0025
0.0020
0.0015
0.0010
Density


0.5
0.4
0.3
0.2
0.1
0.0
Density
0
10
20
30
40
50
60
campaign


0.04
0.03
0.02
0.01
0.00
Density
0
200
400
600
800
pdays



No usual trends in data

Checking distribution for categorical columns

In [15]:

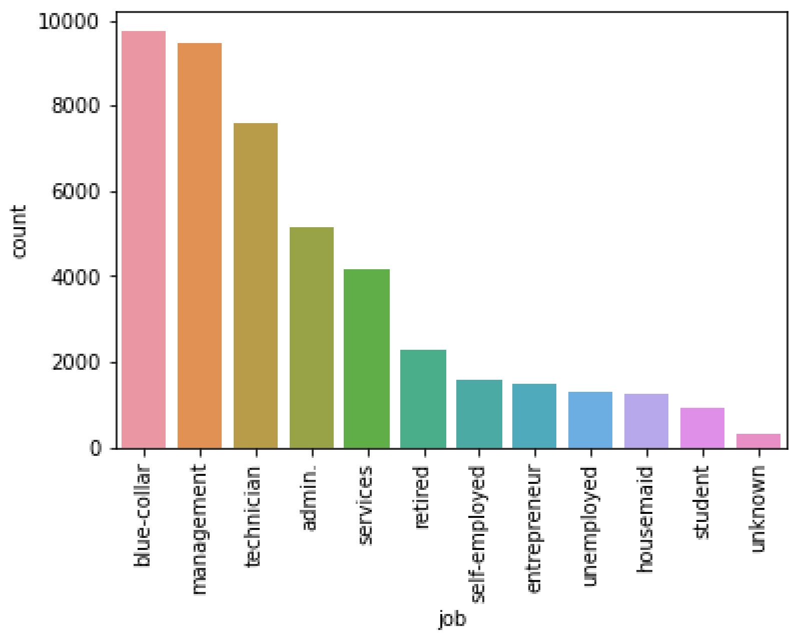
```
df.select_dtypes('object').columns
```

Out[15]:

```
Index(['job', 'marital', 'education', 'targeted', 'default', 'ho
using', 'loan',
       'contact', 'month', 'poutcome', 'response'],
      dtype='object')
```

In [16]:

```
sns.countplot(x = 'job', data = df, order = df['job'].value_counts().index)

plt.xticks(rotation = 90)
plt.show()
```



In [17]:

```
df.loc[df['education'] == 'tertiary', ['job']].value_counts()
```

Out[17]:

```
job
management       7801
technician       1968
self-employed     833
entrepreneur      686
admin.            572
retired           366
unemployed        289
student           223
services          202
housemaid         173
blue-collar       149
unknown            39
dtype: int64
```

In [18]:

```
df.loc[df['education'] == 'secondary', ['job']].value_counts()
```

Out[18]:

```
job
blue-collar      5371
technician       5229
admin.           4219
services         3457
management       1121
retired           984
unemployed        728
self-employed     577
entrepreneur      542
student           508
housemaid         395
unknown            71
dtype: int64
```

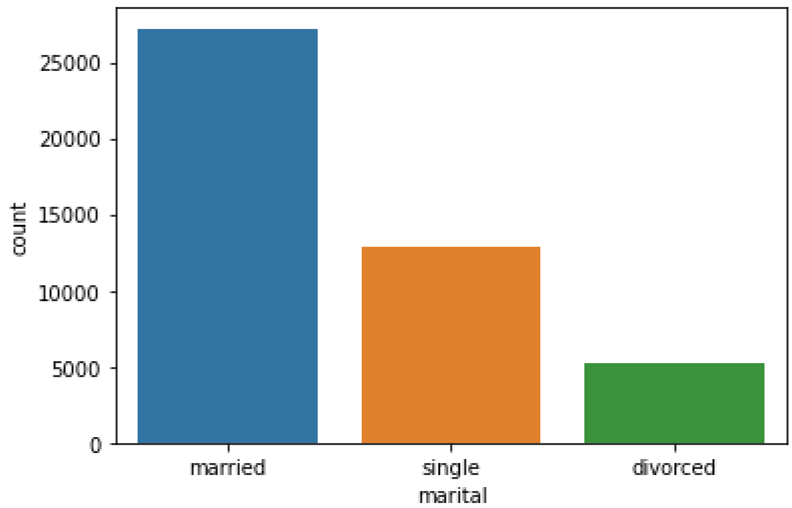
Tertiary less blue collared and entrepreneurs

In [19]:

```
sns.countplot(x = 'marital', data = df)
```

Out[19]:

```
<AxesSubplot:xlabel='marital', ylabel='count'>
```



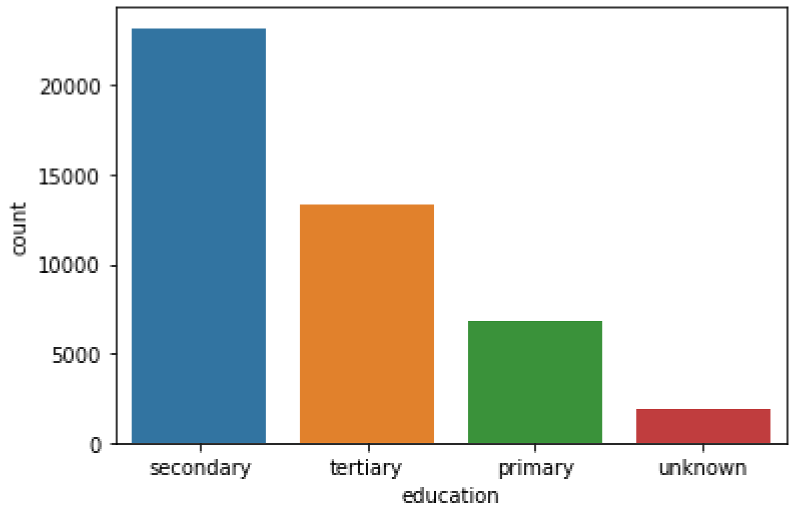
Highest to married approached

In [20]:

```
sns.countplot(x = 'education', data = df, order = df['education'].value_counts(
```

Out[20]:

```
<AxesSubplot:xlabel='education', ylabel='count'>
```

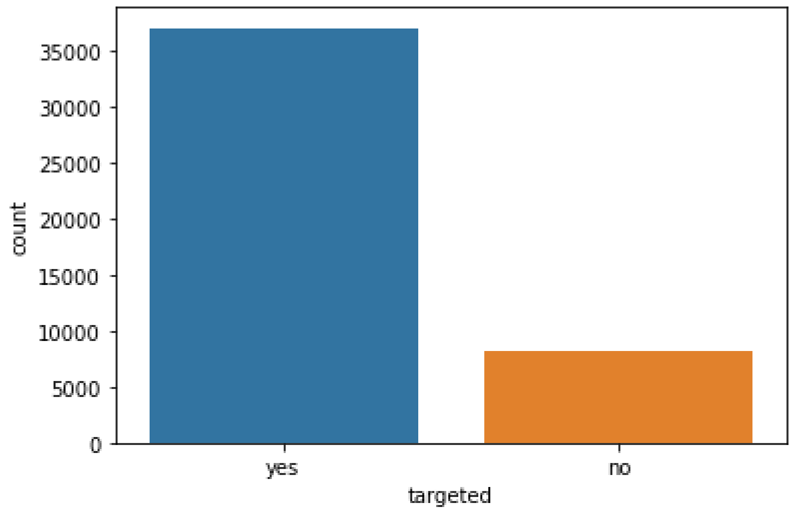


In [21]:

```
sns.countplot(x = 'targeted', data = df)
```

Out[21]:

```
<AxesSubplot:xlabel='targeted', ylabel='count'>
```

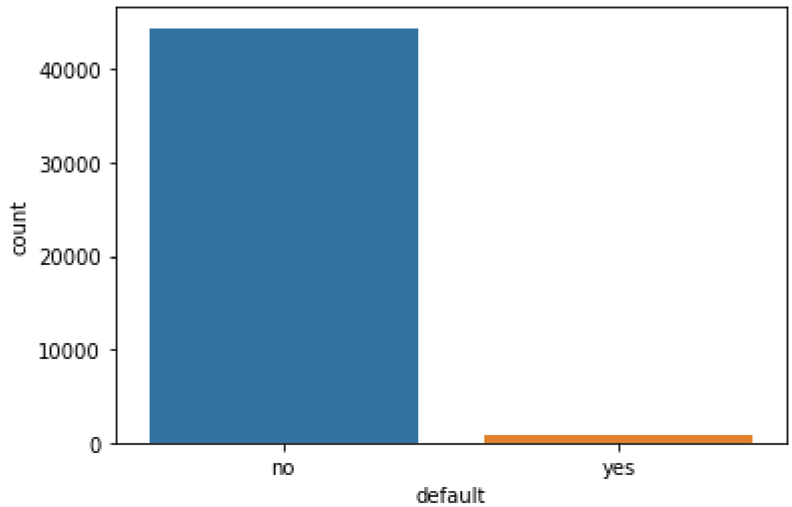


In [22]:

```
sns.countplot(x = 'default', data = df)
```

Out[22]:

```
<AxesSubplot:xlabel='default', ylabel='count'>
```



In [23]:

```
(df['default'].value_counts(normalize = True) * 100).round(2)
```

Out[23]:

```
no     98.2
yes     1.8
Name: default, dtype: float64
```

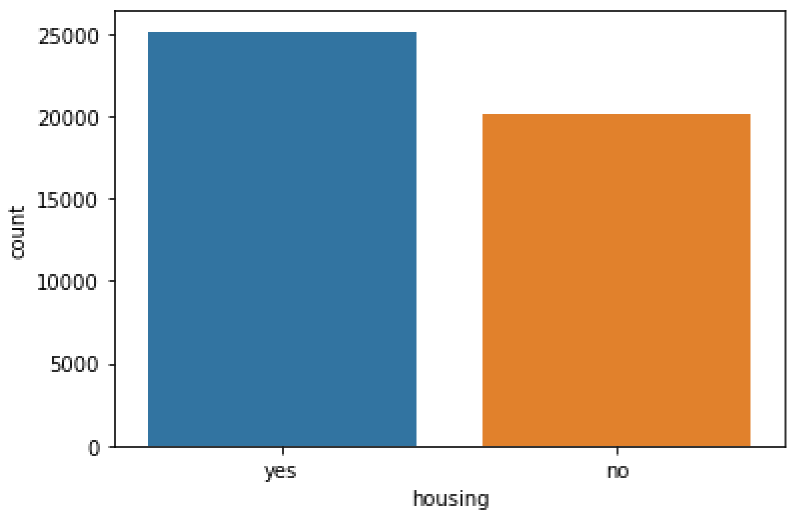
> Every few people have defaulted, which shows that bank are targetting the right customers

In [24]:

```
sns.countplot(x = 'housing', data = df)
```

Out[24]:

```
<AxesSubplot:xlabel='housing', ylabel='count'>
```



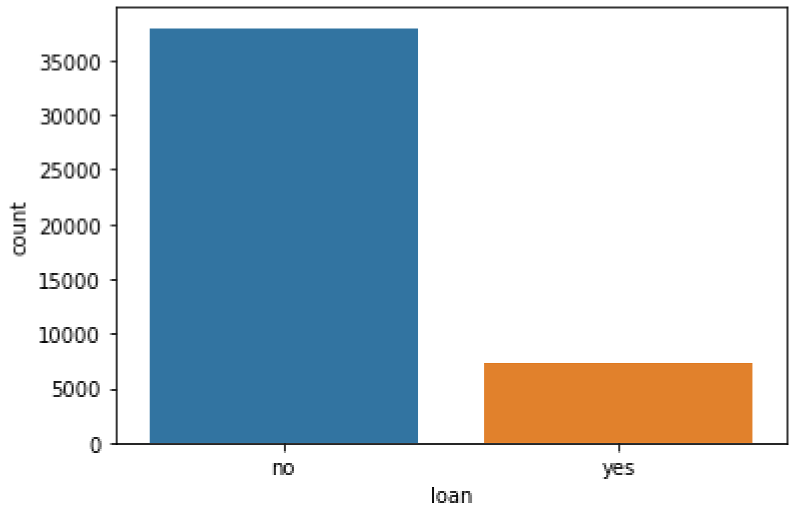
Good balance for with/wothout housing loans

In [25]:

```
sns.countplot(x = 'loan', data = df)
```

Out[25]:

```
<AxesSubplot:xlabel='loan', ylabel='count'>
```



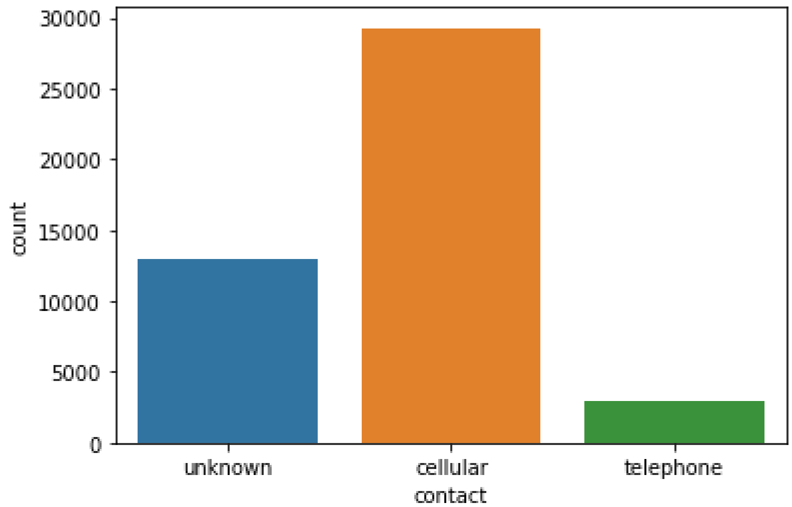
People with no loan history given loans

In [26]:

```
sns.countplot(x = 'contact', data = df)
```

Out[26]:

```
<AxesSubplot:xlabel='contact', ylabel='count'>
```



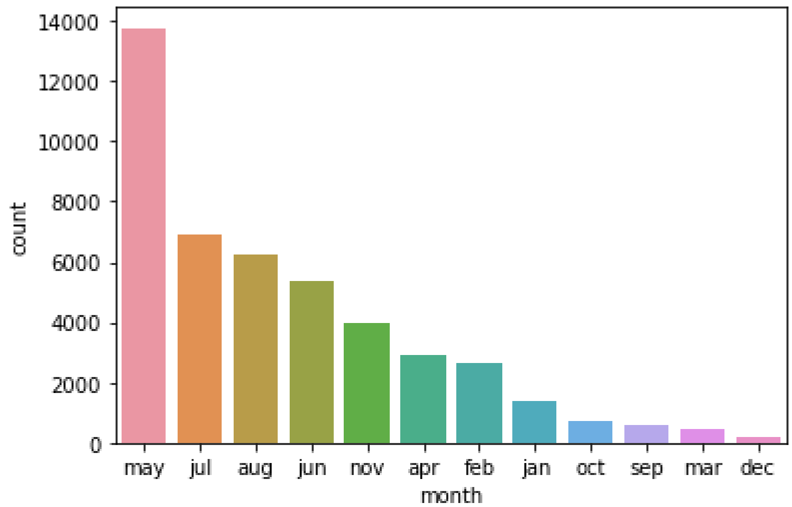
Company performs the highest comunication via cellular, needs to find other methods also to increase success ratio

In [27]:

```
sns.countplot(x = 'month', data = df, order = df['month'].value_counts().index)
```

Out[27]:

```
<AxesSubplot:xlabel='month', ylabel='count'>
```



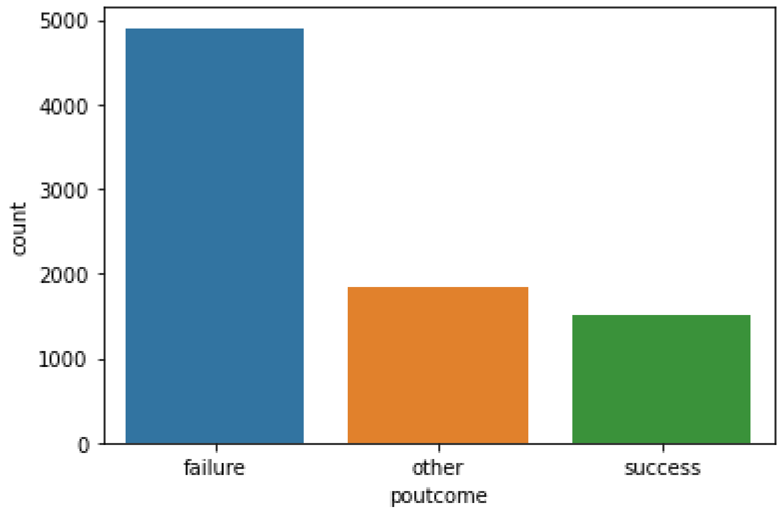
Appraisal season tend to have highest loan takers

In [28]:

```
sns.countplot(x = 'poutcome', data = df[df['poutcome'] != 'unknown'])
```

Out[28]:

```
<AxesSubplot:xlabel='poutcome', ylabel='count'>
```



Many failure even during last campaign

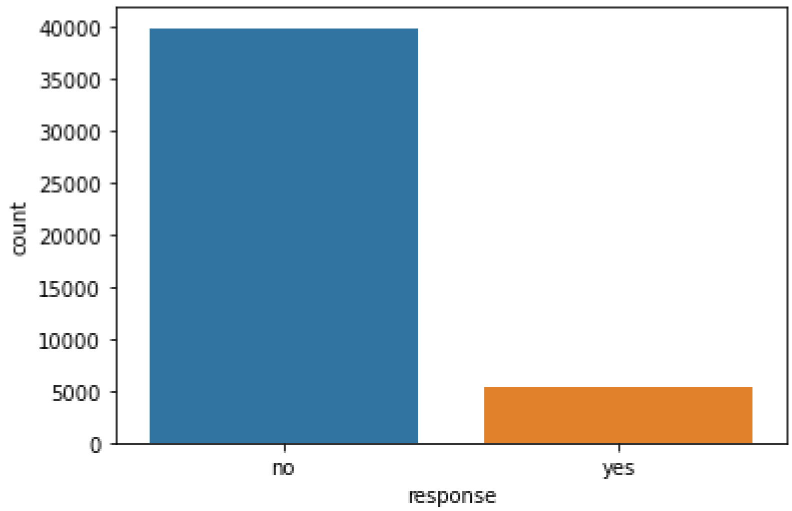
The data from last campaign doesn't seem to matter much

In [29]:

```
sns.countplot(x = 'response', data = df)
```

Out[29]:

```
<AxesSubplot:xlabel='response', ylabel='count'>
```



In [30]:

```
(df['response'].value_counts(normalize = True)*100).round(2)
```

Out[30]:

```
no     88.3
yes    11.7
Name: response, dtype: float64
```

Though the banks are tagetting the right customers, yet they're response rate is very low

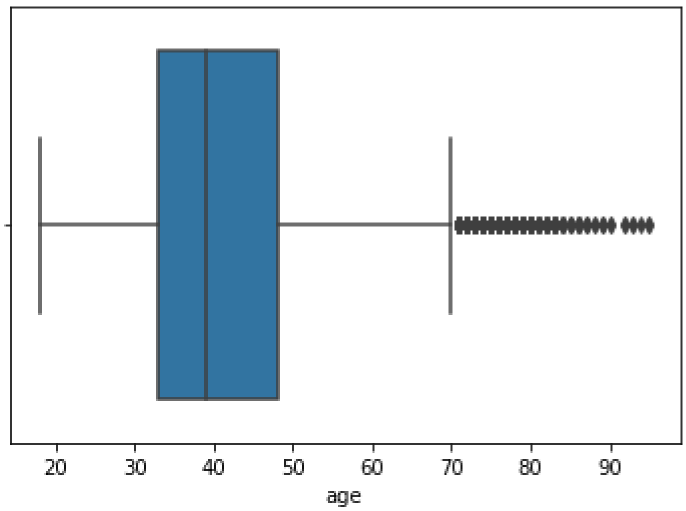
Outlier analysis

In [31]:

```
sns.boxplot('age', data = df)
```

Out[31]:

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



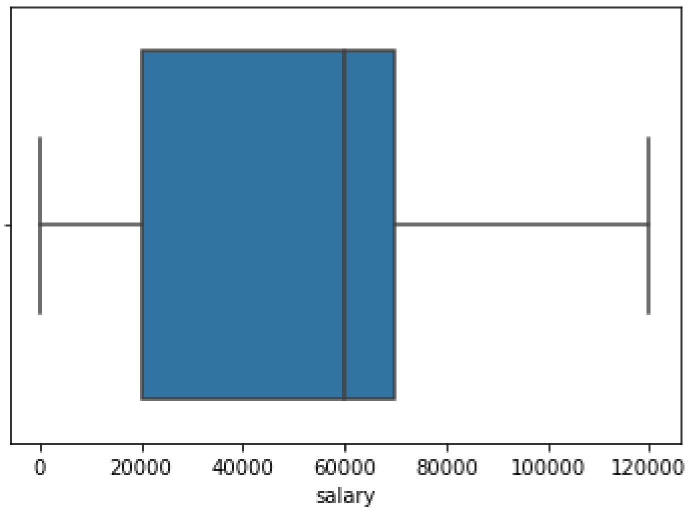
> Majority of the customers lie between 33 - 48 age group
>
> Also, there are coustomers in the post retirement age group, some of which comes out as outliers

In [32]:

```
sns.boxplot('salary', data = df)
```

Out[32]:

<AxesSubplot:xlabel='salary'>



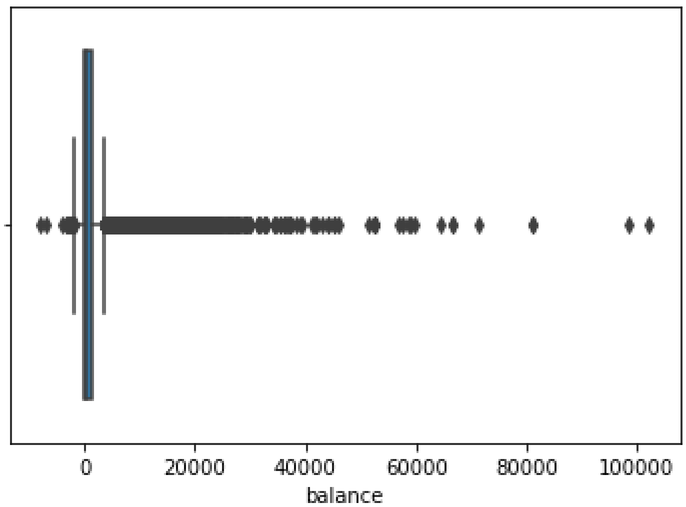
No outliers present

In [33]:

```
sns.boxplot('balance', data = df)
```

Out[33]:

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



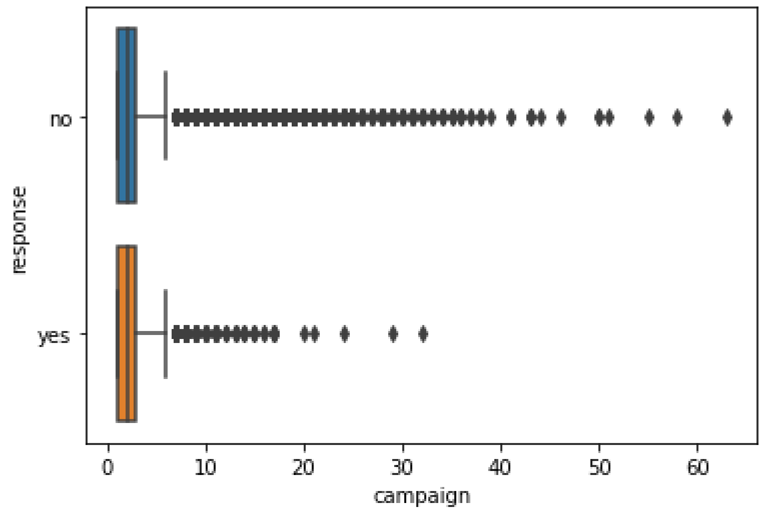
> Many customers targeted have <$5k in their account
>
> Also, some customer have <0 as their balance (risky move, as they have higher defaulting chance)
>
> There are many outliers in the column

In [34]:

```
sns.boxplot(x = 'campaign', data = df, y = 'response')
```

Out[34]:

```
<AxesSubplot:xlabel='campaign', ylabel='response'>
```



> People whom the bank couldn't make as customers tend to have been contacted more times

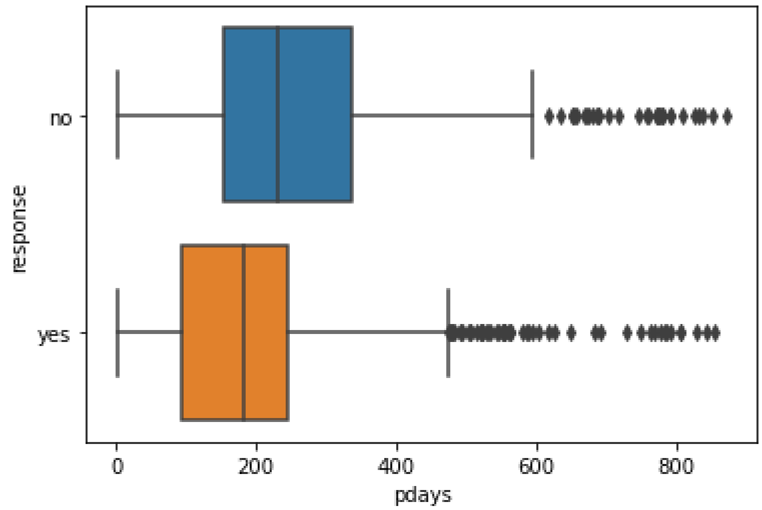
- Which is obviously good that the bank is trying to loop in more customers (but failure ratio must be limited)

In [35]:

```
sns.boxplot(x = 'pdays', data = df[df['pdays'] != -1], y = 'response')
```

Out[35]:

```
<AxesSubplot:xlabel='pdays', ylabel='response'>
```



People who became customer had been contacted on a frequent basis compared to latter.

Bi-variant analysis

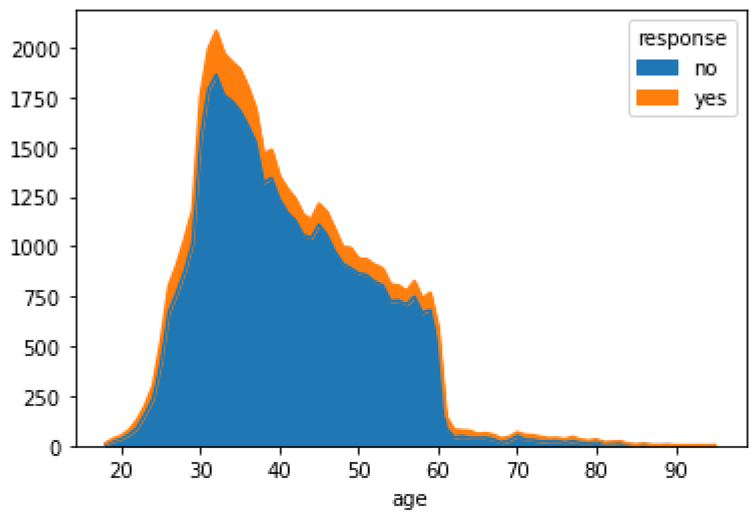
In [36]:

```
col = 'age'

plt.figure(figsize = (9, 4))

pd.crosstab(df[col], df['response']).plot(kind = 'area')
```

Out[36]:

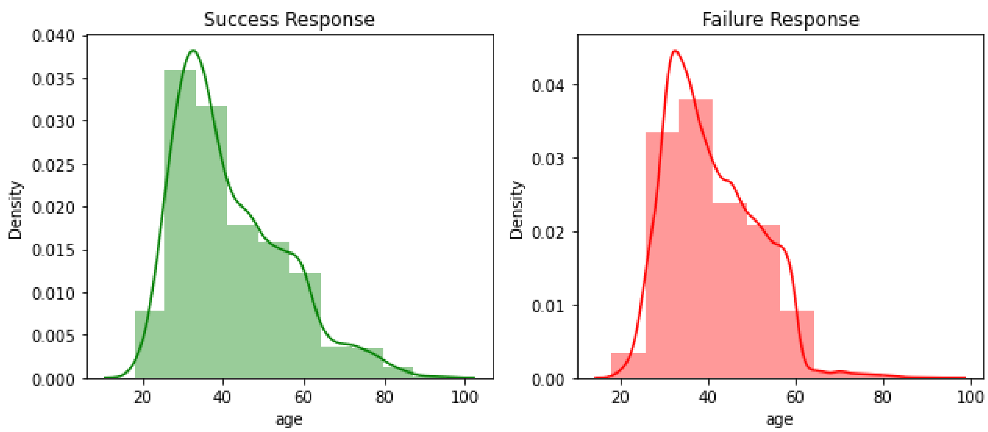
```
<AxesSubplot:xlabel='age'>
```

```
<Figure size 648x288 with 0 Axes>
```



In [37]:

```
col = 'age'

plt.figure(figsize = (9, 4))

plt.subplot(1, 2, 1)
sns.distplot(df.loc[df['response'] == 'yes', col], color = 'g', bins = 10)
plt.title('Success Response')

plt.subplot(1, 2, 2)
sns.distplot(df.loc[df['response'] == 'no', col], color = 'r', bins = 10)
plt.title('Failure Response')

plt.tight_layout()
```

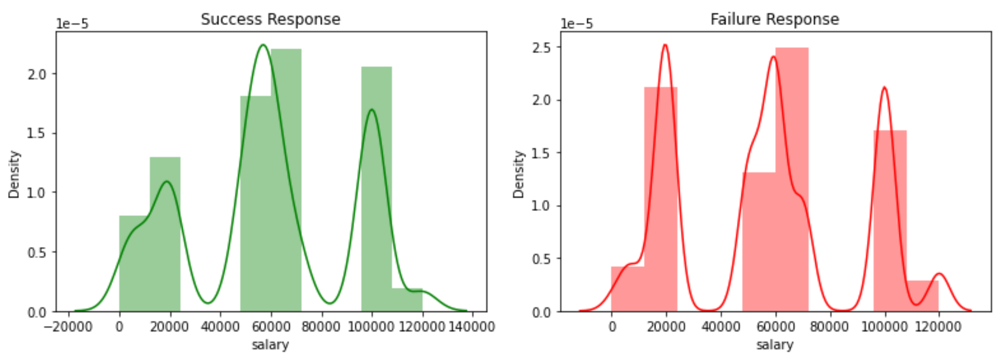


Age group 22-32 tend to take more loans

Group 32 - 40 tend to reject loans

In [38]:

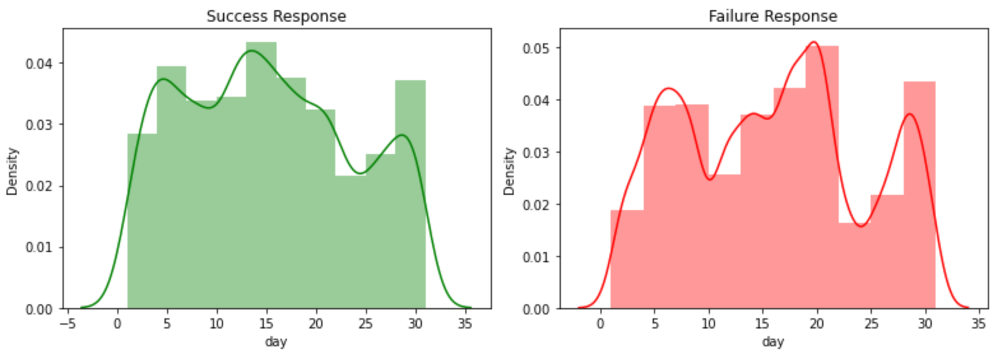
```
col = 'salary'

plt.figure(figsize = (11, 4))

plt.subplot(1, 2, 1)
sns.distplot(df.loc[df['response'] == 'yes', col], color = 'g', bins = 10)
plt.title('Success Response')

plt.subplot(1, 2, 2)
sns.distplot(df.loc[df['response'] == 'no', col], color = 'r', bins = 10)
plt.title('Failure Response')

plt.tight_layout()
```



Salary bin 50000 - 60000 and 95000 - 110000 tend to take loans (higher success ratio)

In [39]:

```
col = 'day'

plt.figure(figsize = (11, 4))

plt.subplot(1, 2, 1)
sns.distplot(df.loc[df['response'] == 'yes', col], color = 'g', bins = 10)
plt.title('Success Response')

plt.subplot(1, 2, 2)
sns.distplot(df.loc[df['response'] == 'no', col], color = 'r', bins = 10)
plt.title('Failure Response')

plt.tight_layout()
```

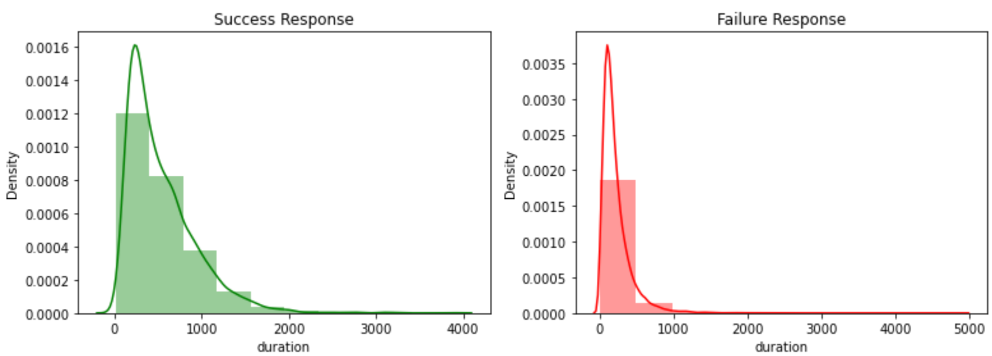


More successful rates during starting and middle of month

From previous analysis we found that 19 of month had high calls, but more failure %

In [40]:

```
col = 'duration'

plt.figure(figsize = (11, 4))

plt.subplot(1, 2, 1)
sns.distplot(df.loc[df['response'] == 'yes', col], color = 'g', bins = 10)
plt.title('Success Response')

plt.subplot(1, 2, 2)
sns.distplot(df.loc[df['response'] == 'no', col], color = 'r', bins = 10)
plt.title('Failure Response')

plt.tight_layout()
```



> Success tends to be higher for duration >5000 seconds

- An inituition can be drwan that people reject the loans if not interested and drop off the call earlier whereas if they are interested tend to know more about the offerings and raises the duration time

In [41]:

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

Out[41]:

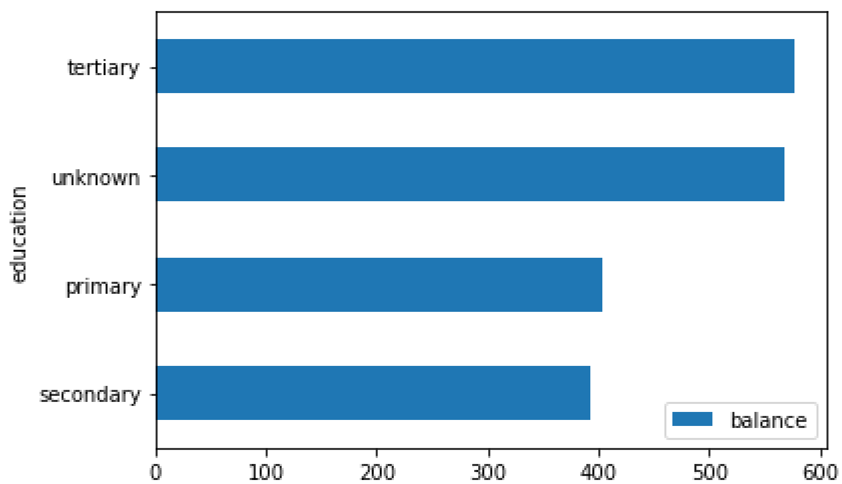
```
count    45211.000000
mean        40.197828
std        100.128746
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

In [42]:

```
df.groupby('education').agg({'balance': 'median'}).sort_values(by = 'balance',
```

Out[42]:

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



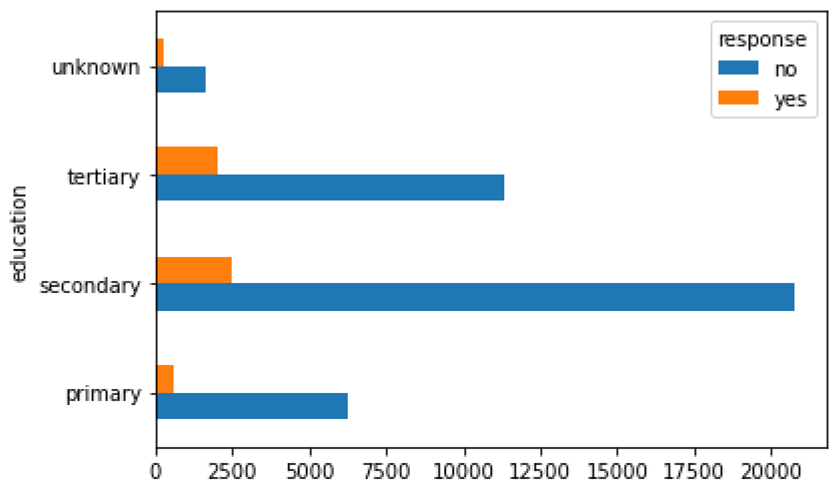
Highest median balance for tertiary educated people

In [43]:

```
col = 'education'

plt.figure(figsize = (9, 4))

pd.crosstab(df[col], df['response']).plot(kind = 'barh')
```

Out[43]:

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

<Figure size 648x288 with 0 Axes>
```



Highest reject is for secondary educated, as expected

In [44]:

```
df.select_dtypes('object').columns
```

Out[44]:

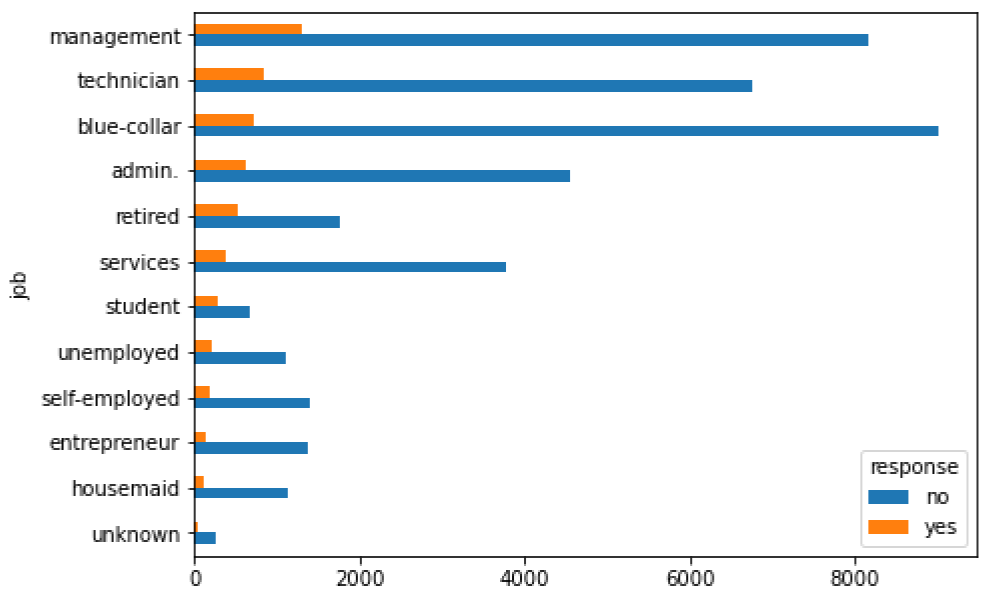
```
Index(['job', 'marital', 'education', 'targeted', 'default', 'ho
using', 'loan',
       'contact', 'month', 'poutcome', 'response'],
      dtype='object')
```

In [45]:

```
col = 'job'

pd.crosstab(df[col], df['response']).sort_values(by = 'yes', ascending = True).
```

Out[45]:

```
<AxesSubplot:ylabel='job'>
```



Though blue-collared are approached (targetted) the highest, they have the highest rejection

The people who were approached (targetted) the second highest -- Management, has the highest response as 'yes' (almost twice as high as blue-collared

We need to hot code target, to pairplot and heatmap analysis

In [46]:

```
df['response'].value_counts()
```

Out[46]:

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

In [47]:

```
# Encoding Yes as 1 and No as 0

df['response'] = df['response'].map({'yes': 1, 'no': 0})
```

In [48]:

```
df['response'].value_counts()
```

Out[48]:

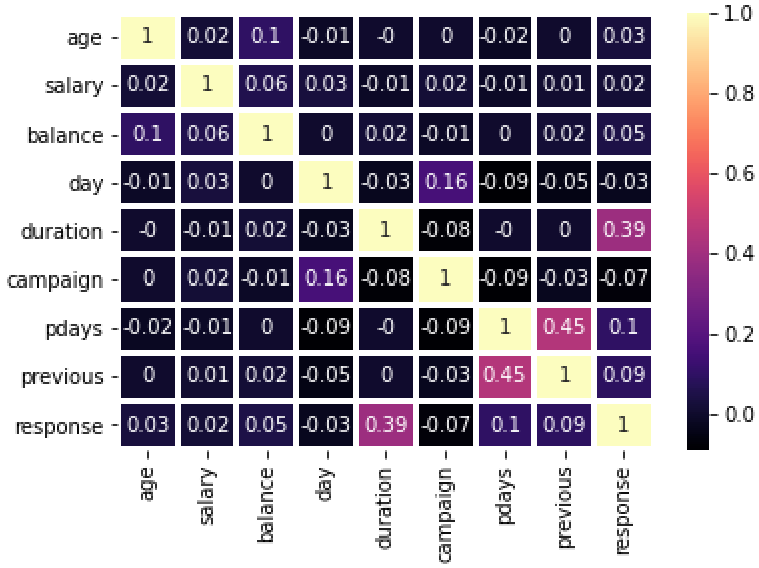
```
0    39922
1     5289
Name: response, dtype: int64
```

In [49]:

```
sns.heatmap(df.corr().round(2), cmap = 'magma', annot = True, linewidths = 2)
```

Out[49]:

```
<AxesSubplot:>
```



pdays and previous have a positive corelation as expected but nearly no co-relation with the target

Dummy Encoding

In [50]:

```
# Finding the columns to encode

df.select_dtypes('object').columns.to_list()
```

Out[50]:

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

In [51]:

```
dummy_df = pd.get_dummies(df[df.select_dtypes('object').columns], drop_first =
dummy_df.head()
```

Out[51]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	jc em
0	0	0	0	1	0	
1	0	0	0	0	0	
2	0	1	0	0	0	
3	1	0	0	0	0	
4	0	0	0	0	0	

5 rows × 36 columns

In [52]:

```
df.shape
```

Out[52]:

```
(45211, 19)
```

In [53]:

```
# Merging the 2 data-frames and removing the redundant columns

df = pd.concat([df.loc[:, ~df.columns.isin(df.select_dtypes('object').columns)]
df.shape
```

Out[53]:

```
(45211, 45)
```

In [54]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 45 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  45211 non-null  int64
 1   salary               45211 non-null  int64
 2   balance              45211 non-null  int64
 3   day                  45211 non-null  int64
 4   duration             45211 non-null  int64
 5   campaign             45211 non-null  int64
 6   pdays                45211 non-null  int64
 7   previous             45211 non-null  int64
 8   response             45211 non-null  int64
 9   job_blue-collar      45211 non-null  uint8
 10  job_entrepreneur     45211 non-null  uint8
 11  job_housemaid        45211 non-null  uint8
 12  job_management       45211 non-null  uint8
 13  job_retired          45211 non-null  uint8
 14  job_self-employed    45211 non-null  uint8
 15  job_services         45211 non-null  uint8
 16  job_student          45211 non-null  uint8
 17  job_technician       45211 non-null  uint8
 18  job_unemployed       45211 non-null  uint8
 19  job_unknown          45211 non-null  uint8
 20  marital_married      45211 non-null  uint8
 21  marital_single       45211 non-null  uint8
 22  education_secondary  45211 non-null  uint8
 23  education_tertiary   45211 non-null  uint8
 24  education_unknown    45211 non-null  uint8
 25  targeted_yes         45211 non-null  uint8
 26  default_yes          45211 non-null  uint8
 27  housing_yes          45211 non-null  uint8
 28  loan_yes             45211 non-null  uint8
 29  contact_telephone    45211 non-null  uint8
 30  contact_unknown      45211 non-null  uint8
 31  month_aug            45211 non-null  uint8
 32  month_dec            45211 non-null  uint8
 33  month_feb            45211 non-null  uint8
 34  month_jan            45211 non-null  uint8
 35  month_jul            45211 non-null  uint8
 36  month_jun            45211 non-null  uint8
 37  month_mar            45211 non-null  uint8
 38  month_may            45211 non-null  uint8
 39  month_nov            45211 non-null  uint8
 40  month_oct            45211 non-null  uint8
```

```
 41   month_sep            45211 non-null   uint8
 42   poutcome_other       45211 non-null   uint8
 43   poutcome_success     45211 non-null   uint8
 44   poutcome_unknown     45211 non-null   uint8
dtypes: int64(9), uint8(36)
memory usage: 4.7 MB
```

Train-Test split

Following 70% Train, 30% Test

In [55]:

```
train, test = train_test_split(df, test_size = 0.3, random_state = 100)
```

In [56]:

```
df.shape
```

Out[56]:

```
(45211, 45)
```

In [57]:

```
train.shape
```

Out[57]:

```
(31647, 45)
```

In [58]:

```
test.shape
```

Out[58]:

```
(13564, 45)
```

In [59]:

```
train.columns
```

Out[59]:

```
Index(['age', 'salary', 'balance', 'day', 'duration', 'campaig
n', 'pdays',
       'previous', 'response', 'job_blue-collar', 'job_entrepren
eur',
       'job_housemaid', 'job_management', 'job_retired', 'job_se
lf-employed',
       'job_services', 'job_student', 'job_technician', 'job_une
mployed',
       'job_unknown', 'marital_married', 'marital_single',
       'education_secondary', 'education_tertiary', 'education_u
nknown',
       'targeted_yes', 'default_yes', 'housing_yes', 'loan_yes',
       'contact_telephone', 'contact_unknown', 'month_aug', 'mon
th_dec',
       'month_feb', 'month_jan', 'month_jul', 'month_jun', 'mont
h_mar',
       'month_may', 'month_nov', 'month_oct', 'month_sep', 'pout
come_other',
       'poutcome_success', 'poutcome_unknown'],
      dtype='object')
```

Scaling Numeric Columns

In [60]:

```
# Scaling being fitted and Transformed for train

vars = ['age', 'salary', 'balance', 'day', 'duration', 'campaign', 'pdays', 'pr

scaler = MinMaxScaler()
train[vars] = scaler.fit_transform(train[vars])

train[vars].head()
```

Out[60]:

	age	salary	balance	day	duration	campaign	pdays	p
18391	0.285714	0.166667	0.116863	1.000000	0.060294	0.016129	0.000000	C
13056	0.103896	0.416667	0.069372	0.233333	0.042515	0.000000	0.000000	C
13415	0.441558	0.500000	0.104035	0.266667	0.049987	0.000000	0.000000	C
21022	0.272727	0.833333	0.078868	0.433333	0.076527	0.016129	0.000000	C
24510	0.415584	0.833333	0.080339	0.533333	0.018294	0.000000	0.159404	C

In [61]:

```
train[vars].describe().round(2)
```

Out[61]:

	age	salary	balance	day	duration	campaign	pdays	p
count	31647.00	31647.00	31647.00	31647.00	31647.00	31647.00	31647.00	3
mean	0.30	0.48	0.09	0.49	0.07	0.03	0.05	
std	0.14	0.27	0.03	0.28	0.07	0.05	0.11	
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
25%	0.19	0.17	0.07	0.23	0.03	0.00	0.00	
50%	0.27	0.50	0.08	0.50	0.05	0.02	0.00	
75%	0.39	0.58	0.09	0.67	0.08	0.03	0.00	
max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	

In [62]:

```
test[vars].head()
```

Out[62]:

	age	salary	balance	day	duration	campaign	pdays	previous
14789	45	20000	0	16	154	2	-1	0
8968	41	100000	5	5	178	1	-1	0
34685	40	100000	906	5	67	4	-1	0
2369	25	50000	768	13	203	1	-1	0
36561	37	70000	0	12	631	1	344	1

In [63]:

```
# Only fitting scaling on test data

test[vars] = scaler.transform(test[vars])
test[vars].head()
```

Out[63]:

	age	salary	balance	day	duration	campaign	pdays	p
14789	0.350649	0.166667	0.072803	0.500000	0.039680	0.016129	0.000000	C
8968	0.298701	0.833333	0.072849	0.133333	0.045864	0.000000	0.000000	C
34685	0.285714	0.833333	0.081029	0.133333	0.017264	0.048387	0.000000	C
2369	0.090909	0.416667	0.079776	0.400000	0.052306	0.000000	0.000000	C
36561	0.246753	0.583333	0.072803	0.366667	0.162587	0.000000	0.395642	C

In [64]:

```
test[vars].describe().round(2)
```

Out[64]:

	age	salary	balance	day	duration	campaign	pdays	p
count	13564.00	13564.00	13564.00	13564.00	13564.00	13564.00	13564.00	1
mean	0.30	0.47	0.08	0.49	0.07	0.03	0.05	
std	0.14	0.27	0.03	0.28	0.07	0.05	0.12	
min	0.00	0.00	0.04	0.00	0.00	0.00	0.00	
25%	0.19	0.17	0.07	0.23	0.03	0.00	0.00	
50%	0.27	0.50	0.08	0.50	0.05	0.02	0.00	
75%	0.39	0.58	0.09	0.67	0.08	0.03	0.00	
max	0.99	1.00	0.68	1.00	1.27	0.92	0.98	

In [65]:

```
# Splitting dependent and independent variables in train data

train_y = train.pop('response')
train_x = train

print(train_y.shape)
print(train_x.shape)
```

```
(31647,)
(31647, 44)
```

In [66]:

```
# Splitting dependent and independent variables in test data

test_y = test.pop('response')
test_x = test

print(test_y.shape)
print(test_x.shape)
```

```
(13564,)
(13564, 44)
```

Model Building

Logistic Regression

In [67]:

```
lr = LogisticRegression()
lr.fit(train_x, train_y)

rfe = RFE(lr, 10)
rfe = rfe.fit(train_x, train_y)
```

In [68]:

```
list(zip(train_x.columns,rfe.support_,rfe.ranking_))
```

Out[68]:

```
[('age', False, 22),
 ('salary', False, 33),
 ('balance', True, 1),
 ('day', False, 16),
 ('duration', True, 1),
 ('campaign', True, 1),
 ('pdays', False, 17),
 ('previous', False, 3),
 ('job_blue-collar', False, 28),
 ('job_entrepreneur', False, 19),
 ('job_housemaid', False, 15),
 ('job_management', False, 31),
 ('job_retired', False, 11),
 ('job_self-employed', False, 20),
 ('job_services', False, 30),
 ('job_student', False, 2),
 ('job_technician', False, 29),
 ('job_unemployed', False, 34),
 ('job_unknown', False, 35),
 ('marital_married', False, 32),
 ('marital_single', False, 21),
 ('education_secondary', False, 13),
 ('education_tertiary', False, 12),
 ('education_unknown', False, 27),
 ('targeted_yes', False, 14),
 ('default_yes', False, 26),
 ('housing_yes', False, 5),
 ('loan_yes', False, 9),
 ('contact_telephone', False, 23),
 ('contact_unknown', True, 1),
 ('month_aug', False, 8),
 ('month_dec', True, 1),
 ('month_feb', False, 25),
 ('month_jan', False, 4),
 ('month_jul', False, 6),
 ('month_jun', True, 1),
 ('month_mar', True, 1),
 ('month_may', False, 10),
 ('month_nov', False, 7),
 ('month_oct', True, 1),
 ('month_sep', True, 1),
 ('poutcome_other', False, 24),
 ('poutcome_success', True, 1),
 ('poutcome_unknown', False, 18)]
```

In [69]:

```
train_x_rfe = train_x[train_x.columns[rfe.support_]]
```

In [70]:

```
vif = pd.DataFrame()
vif['Features'] = train_x_rfe.columns
vif['VIF'] = [variance_inflation_factor(train_x_rfe.values, i) for i in range(t
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[70]:

	Features	VIF
0	balance	2.53
1	duration	1.86
3	contact_unknown	1.72
5	month_jun	1.43
2	campaign	1.29
9	poutcome_success	1.09
8	month_sep	1.04
7	month_oct	1.03
6	month_mar	1.02
4	month_dec	1.01

> VIFs are not high so the model is pretty good at predicting and more stable

- If the business scenario requires VIF <2 then `balance` can be removed and proceeded for further steps

In [71]:

```
train_x_rfe = sm.add_constant(train_x_rfe)
```

In [72]:

```
lr1 = sm.Logit(train_y, train_x_rfe)
```

In [73]:

```
result = lr1.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.247067
         Iterations 8
```

In [74]:

```
# Testing how well model is performing on ---train data--- itself

result.predict(train_x_rfe)
```

Out[74]:

```
18391    0.078505
13056    0.058282
13415    0.070838
21022    0.090502
24510    0.041715
           ...
16304    0.049570
79       0.011314
12119    0.026020
14147    0.075295
38408    0.079565
Length: 31647, dtype: float64
```

In [75]:

```
# Confusion matrix

result.pred_table()
```

Out[75]:

```
array([[27340.,   597.],
       [ 2476.,  1234.]])
```

True Negative - No loan taken

True Positive - Loan taken

False Negative - Model predicts no Loan taken whereas loan was actually taken

False Positive - Model predicts loan taken whereas no Loan was actually taken

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

In [76]:

```
pred_y = (result.predict(train_x_rfe) >= 0.5).astype(int)
```

In [77]:

```
print(classification_report(train_y, pred_y))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     27937
           1       0.67      0.33      0.45      3710

    accuracy                           0.90     31647
   macro avg       0.80      0.66      0.70     31647
weighted avg       0.89      0.90      0.89     31647
```

In [78]:

```
accuracy_score(train_y, pred_y)
```

Out[78]:

```
0.9028975890289759
```

In [79]:

```
precision_score(train_y, pred_y)
```

Out[79]:

```
0.6739486619333698
```

In [80]:

```
recall_score(train_y, pred_y)
```

Out[80]:

```
0.3326145552560647
```

In [81]:

```
f1_score(train_y, pred_y)
```

Out[81]:

```
0.4454069662515791
```

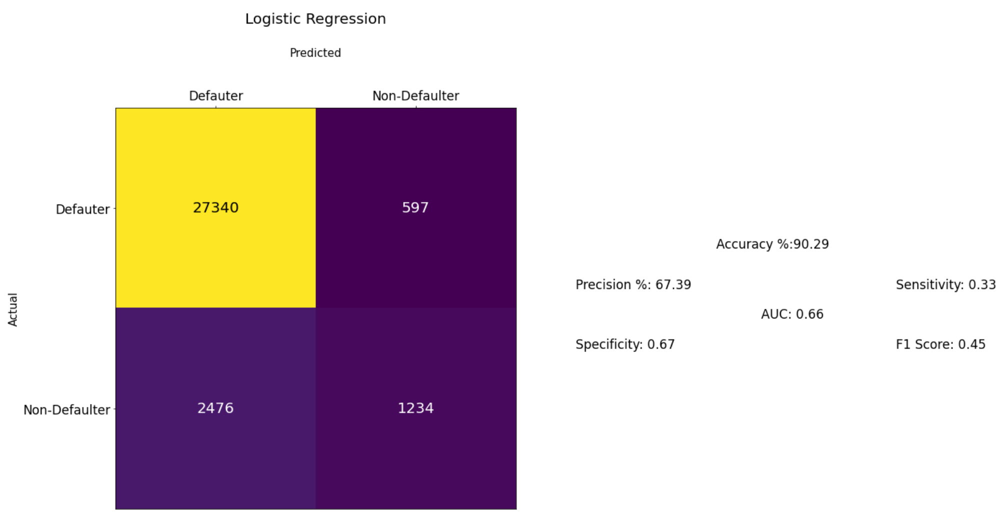
In [82]:

```
def plot_ConfusionMatrix_metrics(conf_mat, test_y, pred_y, figsize = None, clas
                                 hide_ticks = False, title = ''):
    '''
    conf_mat: Output of the confusion_matrix method
    test_y: The true values
    pred_y: The predicted values
    figsize: The size of confusion matrix that needs to be displayed
    class_names: Axes titles
    hide_splines: Option to remove splines. Default False
    hide_ticks: OPtion to hide ticks. Default False
    title: Title of the graph
    '''
    if figsize is None:
        figsize = (len(conf_mat)*5, len(conf_mat)*5)

    fig, ax = plt.subplots(figsize=figsize)

    matshow = ax.matshow(conf_mat)

    for i in range(conf_mat.shape[0]):
        for j in range(conf_mat.shape[1]):
            cell_text = ''
            cell_text += format(conf_mat[i, j], '.0f')
            ax.text(x=j,
                        y=i,
                        s=cell_text,
                        va='center',
                        ha='center',
                        fontsize = 20,
                        color="white" if [i, j] != [0, 0]
                        else "black")

    if hide_spines:
        ax.spines['right'].set_visible(False)
        ax.spines['top'].set_visible(False)
        ax.spines['left'].set_visible(False)
        ax.spines['bottom'].set_visible(False)

    ax.xaxis.set_ticks_position('top')

    ax.set_xticklabels(class_names, fontsize = 17)
    ax.set_yticklabels(class_names, fontsize = 17)
    ax.xaxis.set_label_coords(0.5, 1.15)

    plt.title(title, fontsize = 20, y = 1.2)
    plt.xlabel('Predicted', fontsize = 15)
    plt.ylabel('Actual', fontsize = 15)
```

```
    ax.text(2.5, 0.2, 'Accuracy %:' + str(round(accuracy_score(test_y, pred_y)
    ax.text(1.8, 0.4, 'Precision %: ' + str(round(precision_score(test_y, pred_
    ax.text(3.4, 0.4, 'Sensitivity: ' + str(round(conf_mat[1][1] / (conf_mat[1]
    ax.text(1.8, 0.7, 'Specificity: ' + str(round(conf_mat[1][1] / (conf_mat[0]
    ax.text(3.4, 0.7, 'F1 Score: ' + str(round(f1_score(test_y, pred_y), 2)), f
    ax.text(2.725, 0.55, 'AUC: ' + str(round(roc_auc_score(test_y, pred_y), 2))

    plt.tight_layout()
```

In [83]:

```
plot_ConfusionMatrix_metrics(
    confusion_matrix(train_y, (result.predict(train_x_rfe) >= 0.5).astype(int))
train_y, (result.predict(train_x_rfe) >= 0.5).astype(int),
class_names = ['Defaulter', 'Defauter', 'Non-Defaulter'], title = 'Logistic Reg
```



According to the use case, the False Negatives needs to be handled better as it degrades customer experience where the model's performance needs improvement

Random Forest

In [84]:

```
rm = RandomForestClassifier(50, max_depth = 20)
```

In [85]:

```
rm.fit(train_x_rfe.drop('const', axis = 1), train_y)
```

Out[85]:

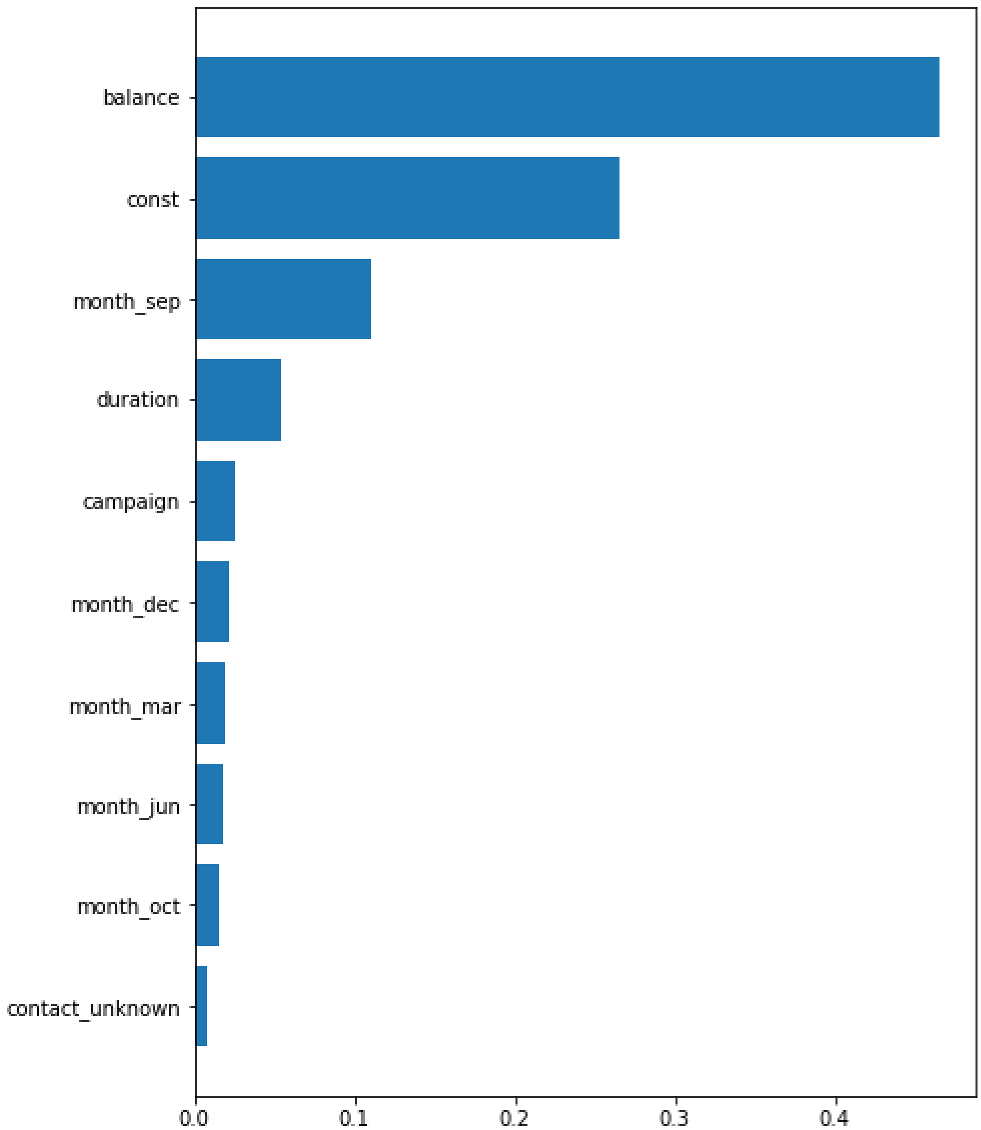
```
RandomForestClassifier(max_depth=20, n_estimators=50)
```

In [86]:

```
pred_y = rm.predict(train_x_rfe.drop('const', axis = 1))
```

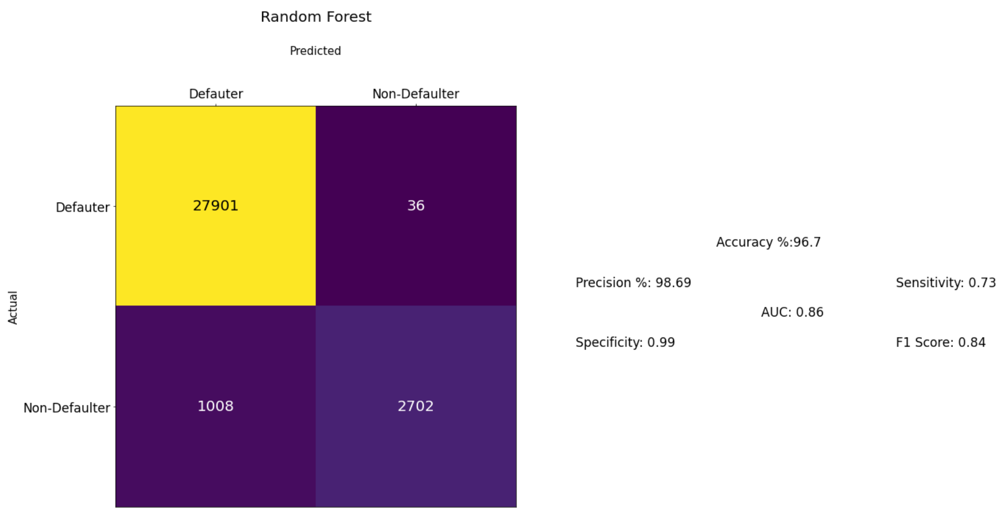
In [87]:

```
importance = rm.feature_importances_

# Plot feature importance

plt.figure(figsize = (7, 10))

temp = dict(zip(train_x_rfe.columns, importance))
temp = sorted(temp, key = temp.get)
plt.barh(temp, sorted(importance))

plt.show()
```



In [88]:

```
plot_ConfusionMatrix_metrics(confusion_matrix(train_y, pred_y), train_y, pred_y
                             class_names = ['Defaulter', 'Defauter', 'Non-Defau
```



In [89]:

```
accuracy_score(train_y, pred_y)
```

Out[89]:

```
0.9670110910986823
```

In [90]:

```
precision_score(train_y, pred_y)
```

Out[90]:

```
0.9868517165814463
```

In [91]:

```
recall_score(train_y, pred_y)
```

Out[91]:

```
0.7283018867924528
```

In [92]:

```
f1_score(train_y, pred_y)
```

Out[92]:

```
0.8380893300248138
```

> The model's accuracy and False Negative rate is really good, but this can be due to overfitting

As seen Random Forest performs better when tested against train data, let's have a look on test data

In [93]:

```
test_x = sm.add_constant(test_x)
```

In [94]:

```
# Testing how well model is performing on ---train data--- itself

result.predict(test_x[train_x_rfe.columns])
```

Out[94]:

```
14789    0.052025
8968     0.033167
34685    0.032213
2369     0.011292
36561    0.838257
           ...
19848    0.079667
27091    0.410732
30831    0.017409
9125     0.021001
9471     0.036497
Length: 13564, dtype: float64
```

In [95]:

```
# Confusion matrix

result.pred_table()
```

Out[95]:

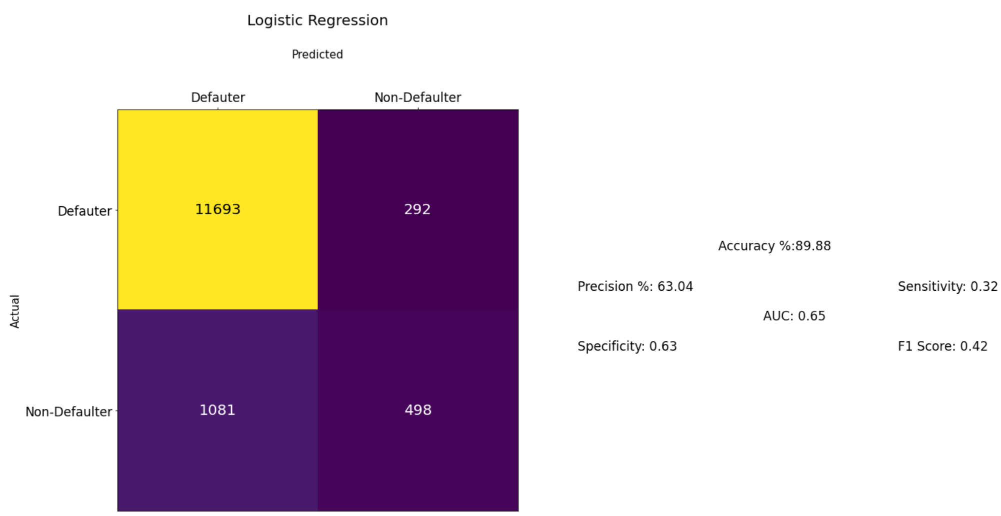
```
array([[27340.,   597.],
       [ 2476.,  1234.]])
```

In [96]:

```
pred_y = (result.predict(test_x[train_x_rfe.columns]) >= 0.5).astype(int)
```

In [97]:

```
plot_ConfusionMatrix_metrics(confusion_matrix(test_y, pred_y), test_y, pred_y,
                             class_names = ['Defaulter', 'Defauter', 'Non-Defau
```



In [98]:

```
print(classification_report(test_y, pred_y))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.94     11985
           1       0.63      0.32      0.42      1579

    accuracy                           0.90     13564
   macro avg       0.77      0.65      0.68     13564
weighted avg       0.88      0.90      0.88     13564
```

In [99]:

```
accuracy_score(test_y, pred_y)
```

Out[99]:

```
0.8987761722205839
```

In [100]:

```
precision_score(test_y, pred_y)
```

Out[100]:

```
0.6303797468354431
```

In [101]:

```
recall_score(test_y, pred_y)
```

Out[101]:

```
0.31538948701709946
```

In [102]:

```
f1_score(test_y, pred_y)
```

Out[102]:

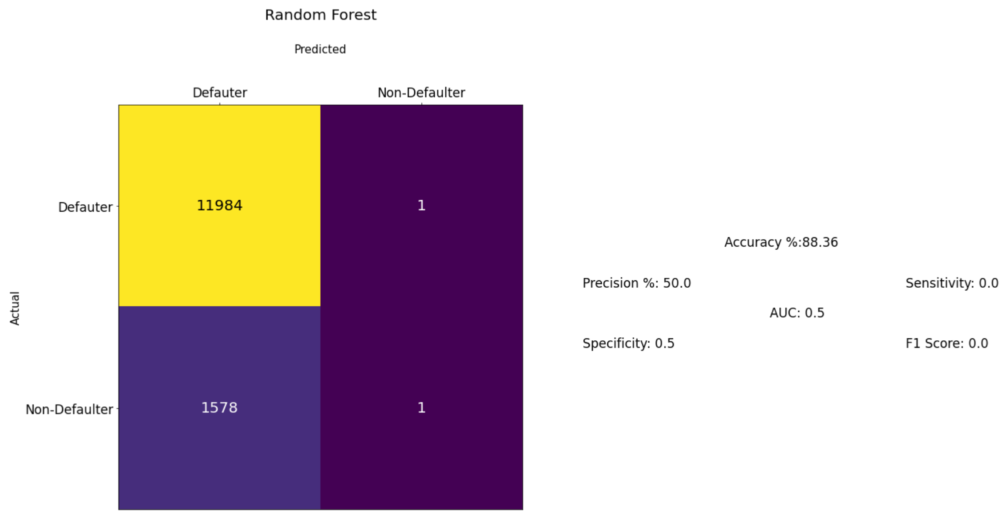
```
0.42043056141831997
```

In [103]:

```
pred_y = rm.predict(test_x[temp])
```

In [104]:

```
plot_ConfusionMatrix_metrics(confusion_matrix(test_y, pred_y), test_y, pred_y,
                                  class_names = ['Defaulter', 'Defauter', 'Non-Defau
```



In [105]:

```
accuracy_score(test_y, pred_y)
```

Out[105]:

```
0.8835889118254202
```

In [106]:

```
precision_score(test_y, pred_y)
```

Out[106]:

```
0.5
```

In [107]:

```
recall_score(test_y, pred_y)
```

Out[107]:

```
0.0006333122229259025
```

In [108]:

```
f1_score(test_y, pred_y)
```

Out[108]:

```
0.0012650221378874128
```

In [109]:

```
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics
```

In [110]:

```
df_mod = sm.add_constant(df)

scores = cross_val_score(rm, df_mod[train_x_rfe.columns], df['response'], cv=6)
print ("Cross-validated scores:", scores)
```

```
Cross-validated scores: [0.89822187 0.63092236 0.89250166 0.8818
8454 0.86914399 0.75009954]
```

In [111]:

```
skf = StratifiedKFold(shuffle=True, n_splits=5)
cv_results_skfold = cross_val_score(rm, df_mod[train_x_rfe.columns], df['respon
```

In [112]:

```
print(cv_results_skfold)
```

```
[0.89594161 0.90079628 0.89902676 0.89703605 0.89659367]
```

In [113]:

```
print(cv_results_skfold.mean())
```

```
0.8978788776462665
```

In [114]:

```
skf = StratifiedKFold(shuffle=True, n_splits=5)
cv_results_skfold = cross_val_score(rm, df_mod[train_x_rfe.columns], df['respon
```

In [115]:

```
print(cv_results_skfold)
```

```
[0.40548204 0.4153264  0.44801512 0.39224953 0.42155009]
```

In [116]:

```
print(cv_results_skfold.mean())
```

```
0.416524636369652
```

In [117]:

```
skf = StratifiedKFold(shuffle=True, n_splits=5)
cv_results_skfold = cross_val_score(rm, df_mod[train_x_rfe.columns], df['respon
```

In [118]:

```
print(cv_results_skfold)
```

```
[0.63181149 0.61884058 0.57412399 0.57571802 0.60026212]
```

In [119]:

```
print(cv_results_skfold.mean())
```

```
0.6001512390547526
```

In [120]:

```
skf = StratifiedKFold(shuffle=True, n_splits=5)
cv_results_skfold = cross_val_score(rm, df_mod[train_x_rfe.columns], df['respon
```

In [121]:

```
print(cv_results_skfold)
```

```
[0.48654709 0.47418101 0.45798082 0.48481375 0.5105673 ]
```

In [122]:

```
print(cv_results_skfold.mean())
```

```
0.48281799395857405
```

	Logisitc Regression	Random Forest
Accuracy	89.88 %	89.78%
Sensitivity	0.32	0.41

The accuracy of logistic regression is better compared to random forest but sensitivity of random forest is better.

Both the models tend to give the iportance to the same set of variables

In [ ]:

```

```