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In [1]:
```
##importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

In [95]:
```
df = pd.read_csv('C:/Users/vikas/Downloads/ML Project1_BMP/bank-marketing.csv'
)
```

In [96]:
```
df.head()
```

Out[96]:

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

In [4]:
```
df.shape
```

Out[4]: (45211, 19)

In [5]:
```
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 [6]:
```
df.response.value_counts()
```

Out[6]:
```
no     39922
yes     5289
Name: response, dtype: int64
```

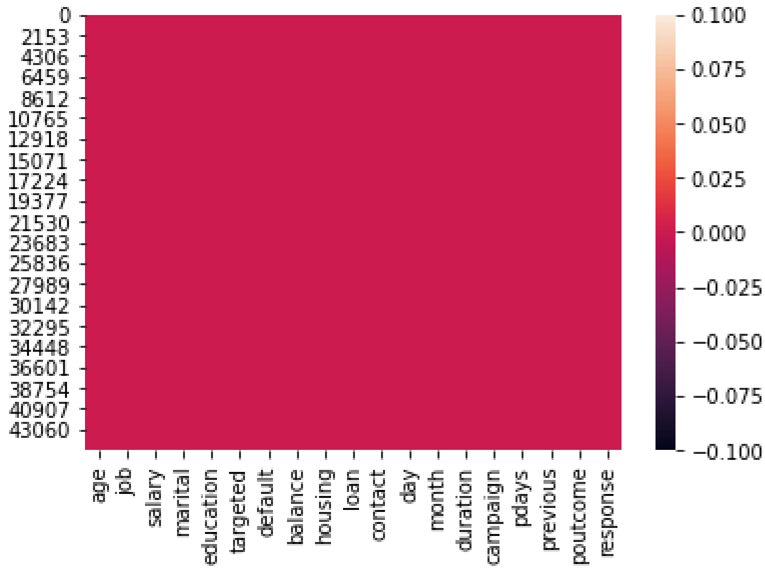
In [7]:
```
df.describe()
```

Out[7]:

	age	salary	balance	day	duration	campaign
count	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
std	10.618762	32085.718415	3044.765829	8.322476	257.527812	3.098021
min	18.000000	0.000000	-8019.000000	1.000000	0.000000	1.000000
25%	33.000000	20000.000000	72.000000	8.000000	103.000000	1.000000
50%	39.000000	60000.000000	448.000000	16.000000	180.000000	2.000000
75%	48.000000	70000.000000	1428.000000	21.000000	319.000000	3.000000
max	95.000000	120000.000000	102127.000000	31.000000	4918.000000	63.000000

In [8]:
```
sns.heatmap(df.isnull())
```

Out[8]:
```
<AxesSubplot:>
```



In [9]:
```
df.isnull().sum()
```

Out[9]:
```
age          0
job          0
salary       0
marital      0
education    0
targeted     0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
response     0
dtype: int64
```

In [10]:
```
# 1 -Describe the pdays column, make note of the mean, median and minimum valu
es. Anything fishy in the values?
```

In [11]:
```
df.pdays.describe()
```

Out[11]:
```
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
```

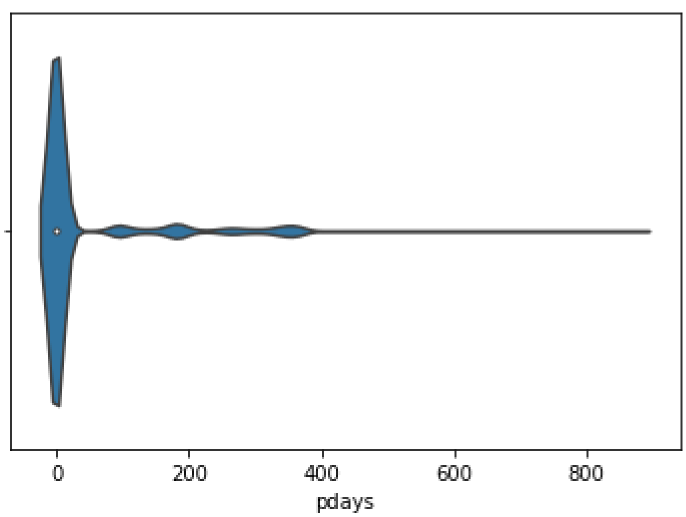
In [12]:
```
print('median',df.pdays.median())
print('mean:',df.pdays.mean())
print('mode:',df.pdays.mode())
```

```
median -1.0
mean: 40.19782796222158
mode: 0   -1
dtype: int64
```

In pdays column most of the records contain -1 values

In [13]:
```
sns.violinplot(df['pdays'])
```

Out[13]: <AxesSubplot:xlabel='pdays'>



In [14]:
```
#2 - Describe the pdays column again, this time limiting yourself to the relev
ant values of pdays.
#How different are the mean and the median values?
```

In [15]:
```
df.pdays.value_counts()
```

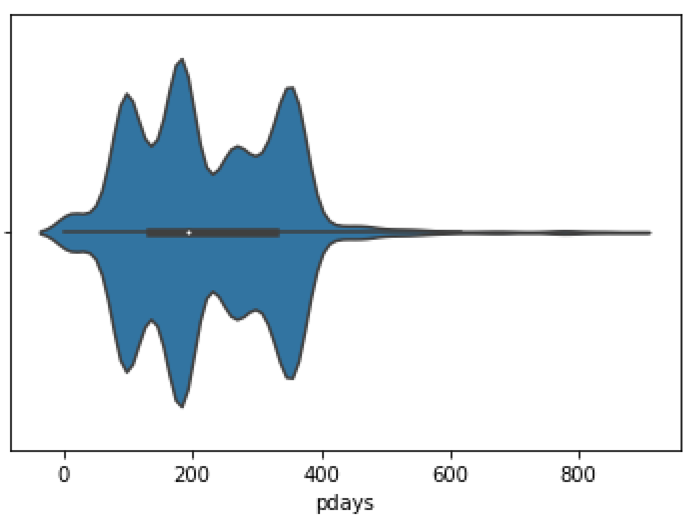
Out[15]:
```
-1      36954
 182      167
 92       147
 183      126
 91       126
         ...
 749        1
 717        1
 589        1
 493        1
 32         1
Name: pdays, Length: 559, dtype: int64
```

In [16]:
```
df.pdays[df['pdays'] != -1].describe()
```

Out[16]:
```
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 [17]:
```
sns.violinplot(df.pdays[df['pdays'] != -1])
```

Out[17]:
```
<AxesSubplot:xlabel='pdays'>
```



In [18]:
```
pdays= df[df['pdays'] != -1]
```

In [19]:
```
print('median',pdays.pdays.median())
print('mean:',pdays.pdays.mean())
print('mode:',pdays.pdays.mode())
```

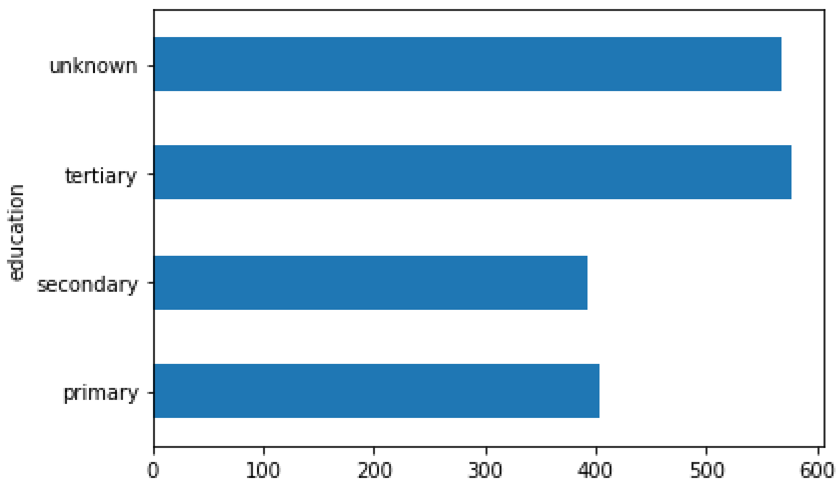
```
median 194.0
mean: 224.57769165556496
mode: 0    182
dtype: int64
```

As there are no values for customers who were not approached (-1). The mean median and mode have changed significantly.

In [20]:
```
#Plot a horizontal bar graph with the median values of balance for each educat
ion level value.
#Which group has the highest median?
```

In [21]:
```
df.groupby(['education'])['balance'].median().plot.barh()
```

Out[21]: <AxesSubplot:ylabel='education'>

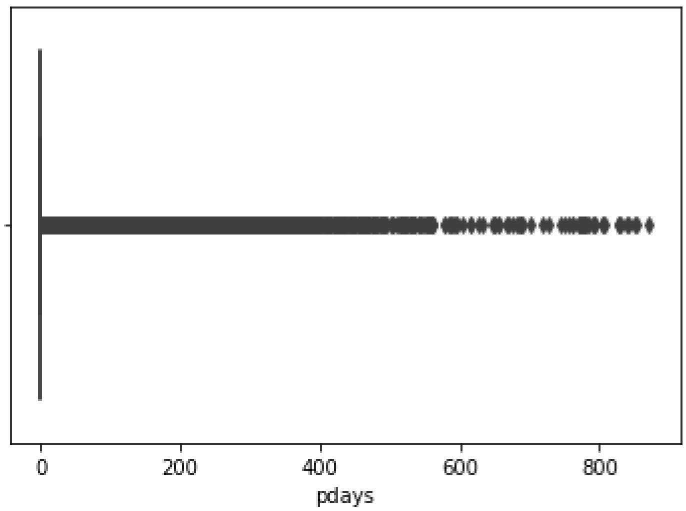


tertiary level education has is the highest median

In [22]:
```
#Make a box plot for pdays. Do you see any outliers?
```

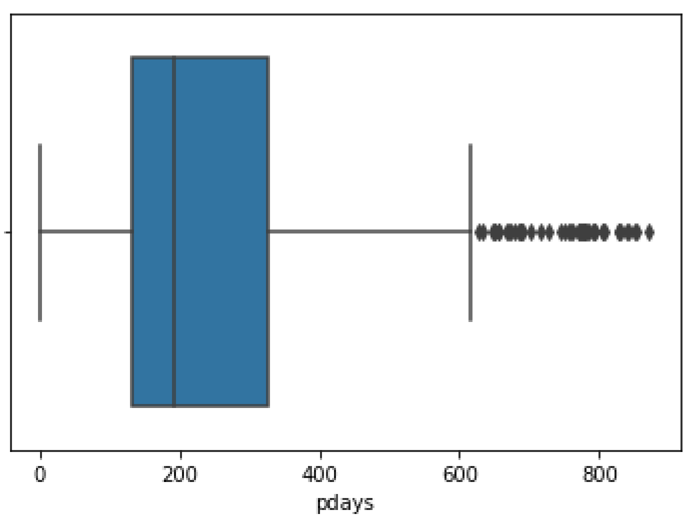
In [23]:
```
sns.boxplot('pdays',data=df)
print('outliers with having -1 values')
```

```
outliers with having -1 values
```



In [24]:
```
sns.boxplot('pdays',data=df[df['pdays'] != -1])
print('outliers without -1 values')
```

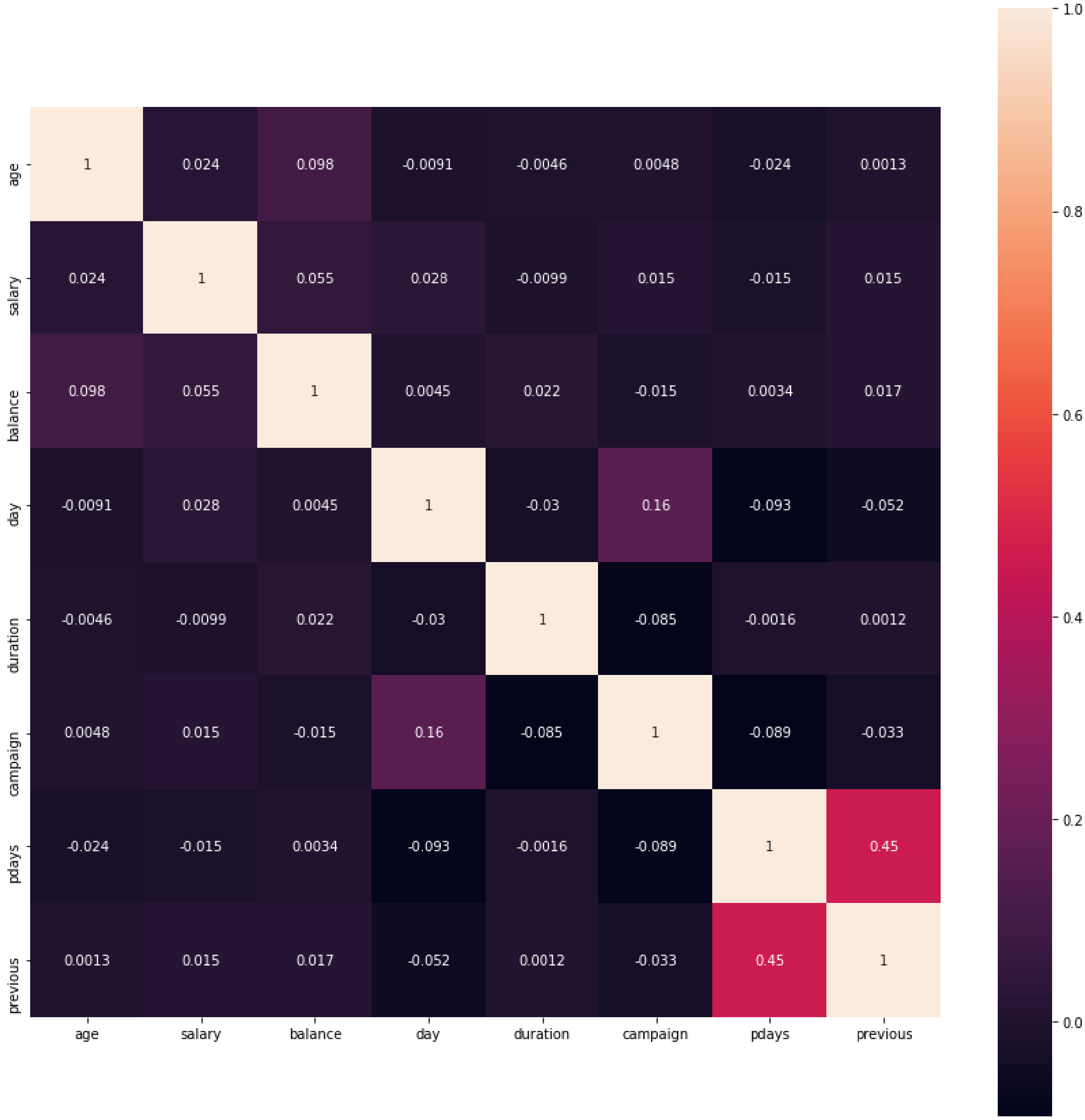
```
outliers without -1 values
```



There much more outliers in pdyas

In [25]:
```
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(),square=True,annot=True)
```

Out[25]: <AxesSubplot:>



In [26]:
```
df.nunique()
```

Out[26]:
```
age             77
job             12
salary          11
marital          3
education        4
targeted         2
default          2
balance       7168
housing          2
loan             2
contact          3
day             31
month           12
duration      1573
campaign        48
pdays          559
previous        41
poutcome         4
response         2
dtype: int64
```

In [27]:
```
df1=df.drop(df[df['pdays'] < 0].index)
```

In [28]:
```
df1.shape
```

Out[28]:
```
(8257, 19)
```

In [29]:
```
##replacing response into 1 and 0
df1.replace({'response':{'yes':1,'no':0}},inplace=True)
```

In [30]:
```
df1.head()
```

Out[30]:

	age	job	salary	marital	education	targeted	default	balance	housing	loan
24060	33	admin.	50000	married	tertiary	yes	no	882	no	no
24062	42	admin.	50000	single	secondary	yes	no	-247	yes	yes
24064	33	services	70000	married	secondary	yes	no	3444	yes	no
24072	36	management	100000	married	tertiary	yes	no	2415	yes	no
24077	36	management	100000	married	tertiary	yes	no	0	yes	no

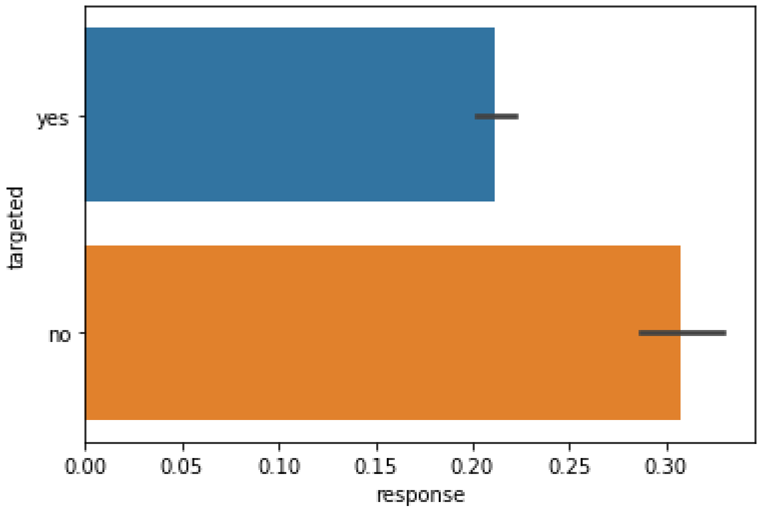
In [31]:
```
##separating categorical and numerical
cols = df1.columns
num_cols= df1._get_numeric_data().columns
cat_cols = list(set(cols) - set(num_cols))
```

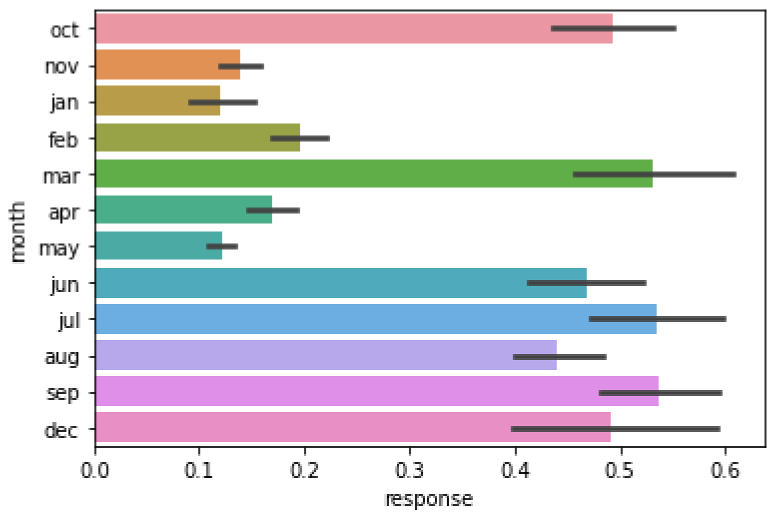
In [32]:
```
print(num_cols)
print(cat_cols)
```

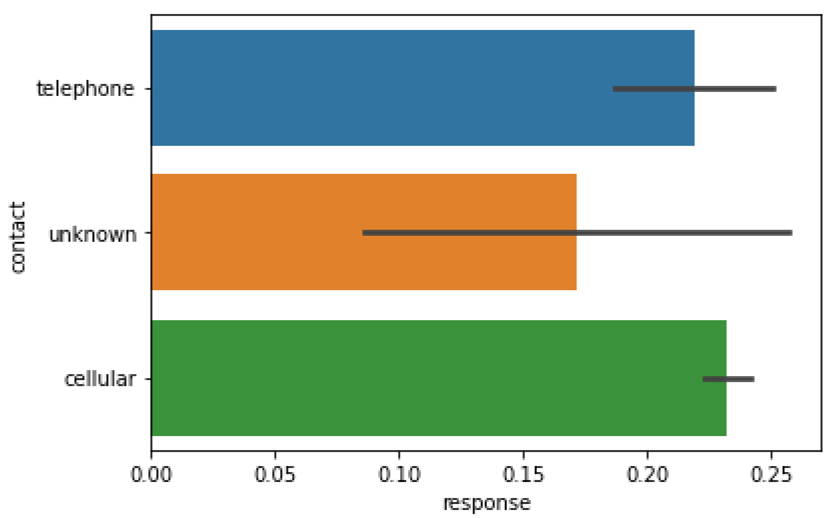
```
Index(['age', 'salary', 'balance', 'day', 'duration', 'campaign', 'pdays',
       'previous', 'response'],
      dtype='object')
['targeted', 'month', 'contact', 'education', 'loan', 'job', 'poutcome', 'mar
ital', 'housing', 'default']
```

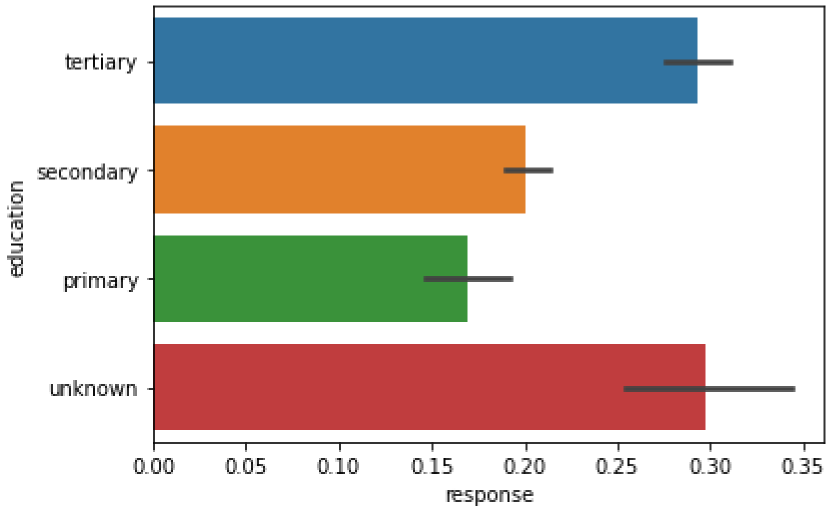
In [33]:
```
#visualizing categorical features with response
```

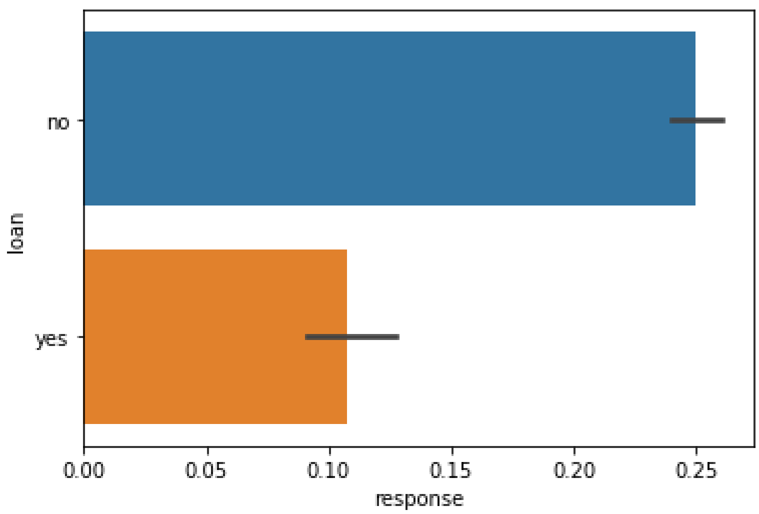
In [34]:
```
for i in df1[cat_cols]:
    sns.barplot(df1.response,df1[i])
    plt.show()
```

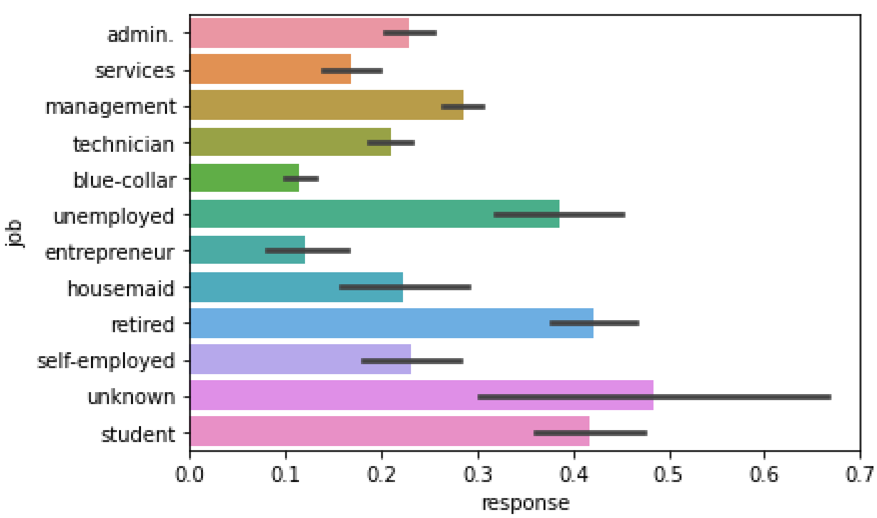

yes
no
targeted
0.00
0.05
0.10
0.15
0.20
0.25
0.30
response

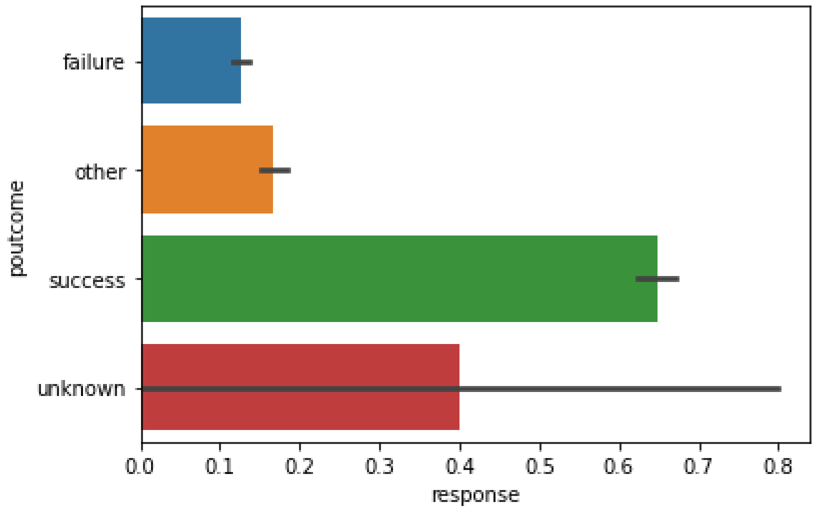

oct
nov
jan
feb
mar
apr
may
jun
jul
aug
sep
dec
month
0.0
0.1
0.2
0.3
0.4
0.5
0.6
response

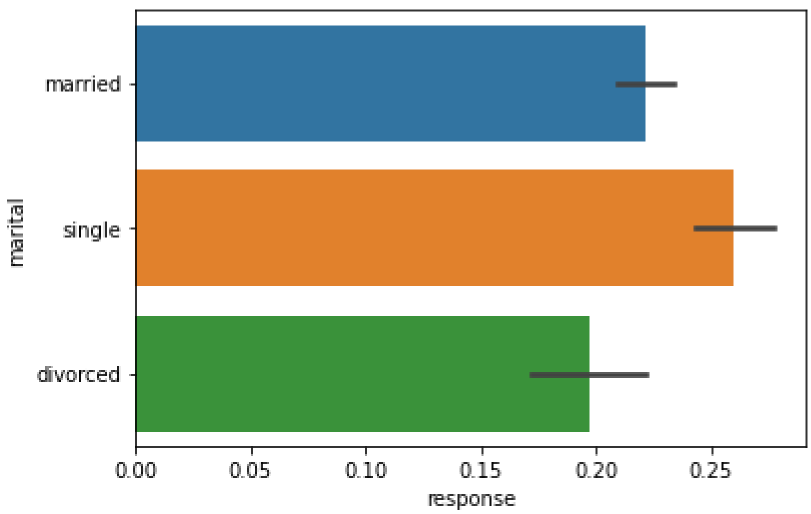

telephone
unknown
cellular
contact
0.00
0.05
0.10
0.15
0.20
0.25
response

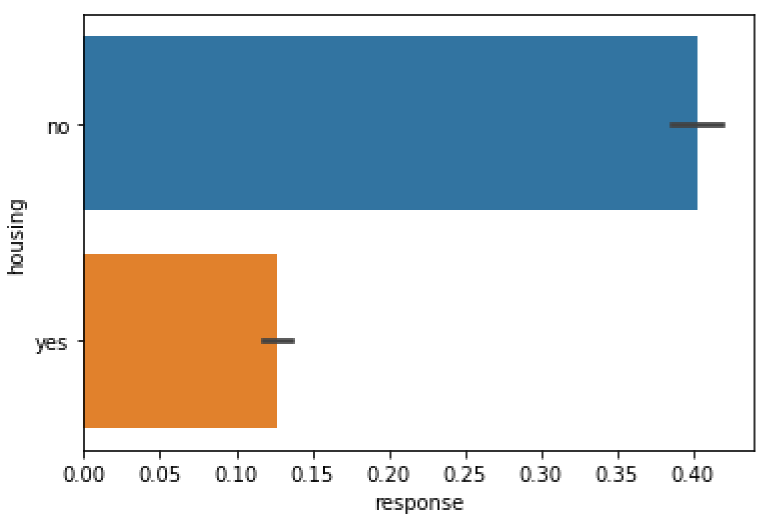

tertiary
secondary
primary
unknown
education
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
response

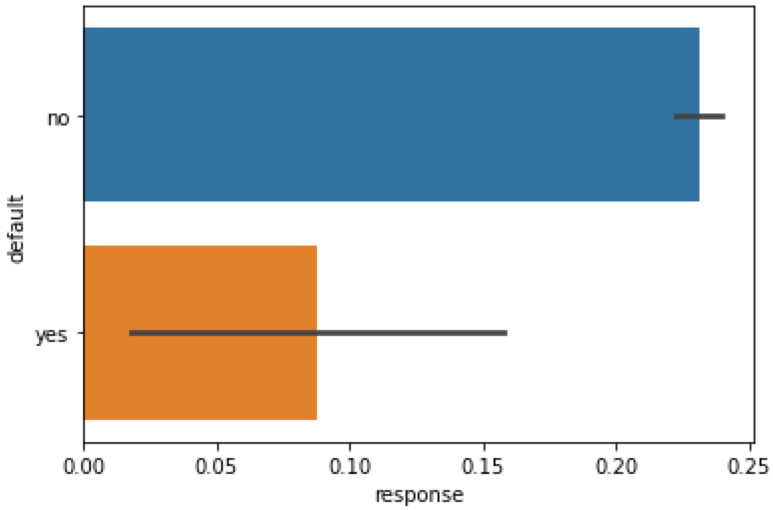

no
yes
loan
0.00
0.05
0.10
0.15
0.20
0.25
response


admin.
services
management
technician
blue-collar
unemployed
entrepreneur
housemaid
retired
self-employed
unknown
student
job
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
response


failure
other
success
unknown
poutcome
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8
response

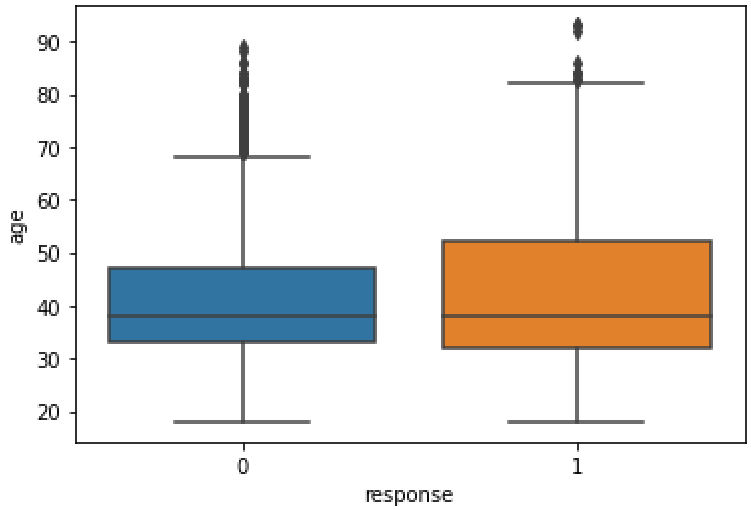

married
single
divorced
marital
0.00 0.05 0.10 0.15 0.20 0.25
response

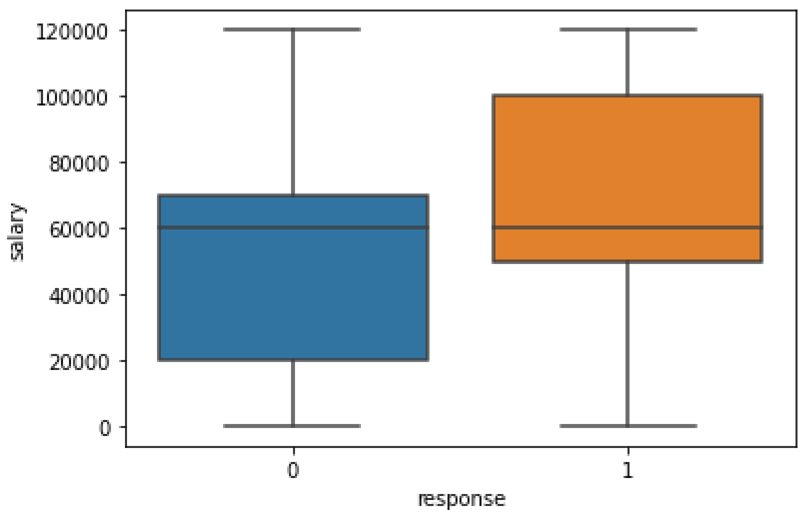

no
yes
housing
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
response

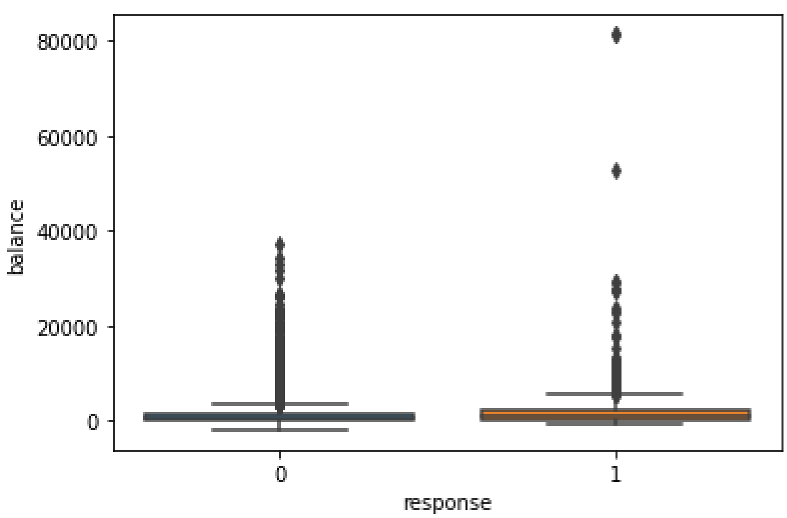


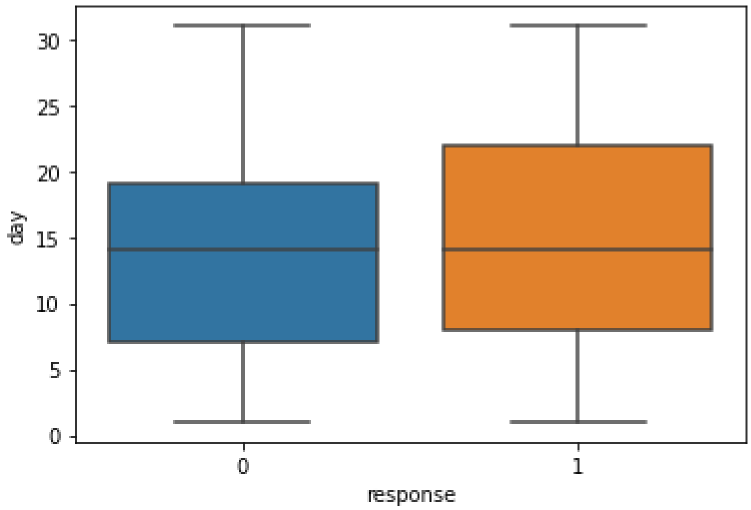
In [35]:
```
#visualizing numercal features with response
```

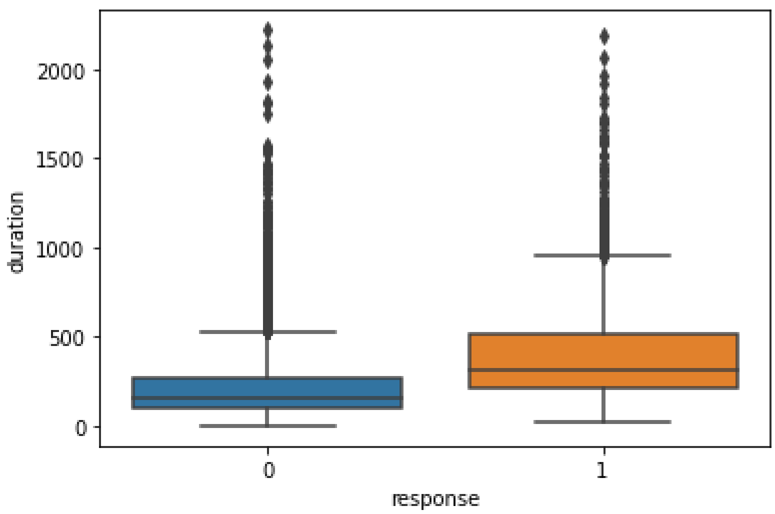
In [36]:
```
for i in df1[num_cols]:
    sns.boxplot(df1.response,df1[i])
    plt.show()
```

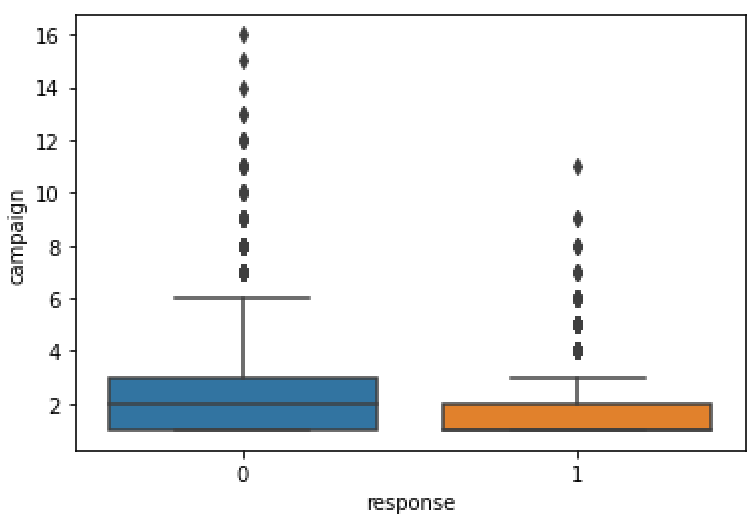

age
90
80
70
60
50
40
30
20
0
1
response

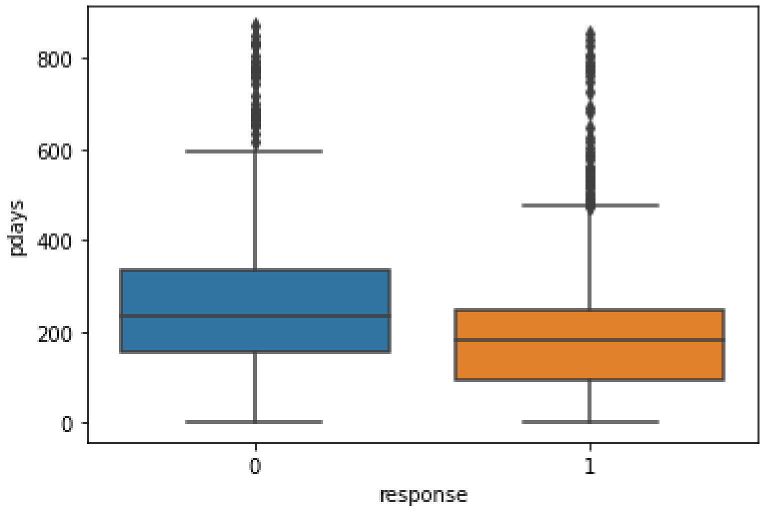

salary
120000
100000
80000
60000
40000
20000
0
0
1
response

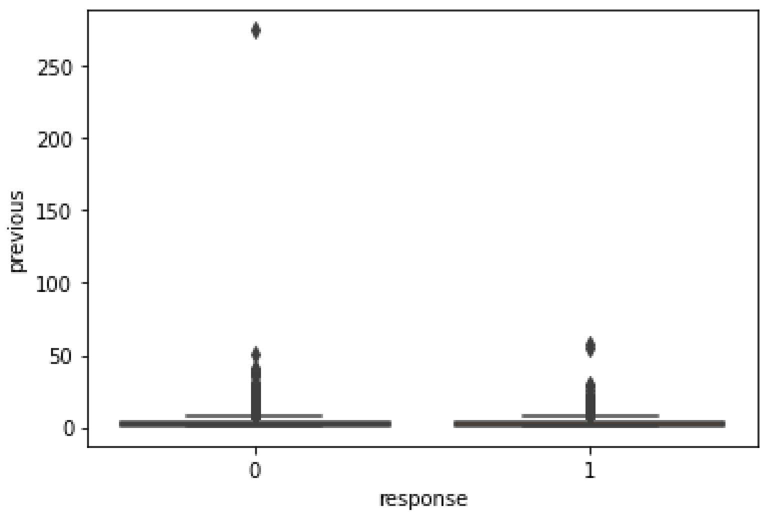

balance
80000
60000
40000
20000
0
0
1
response

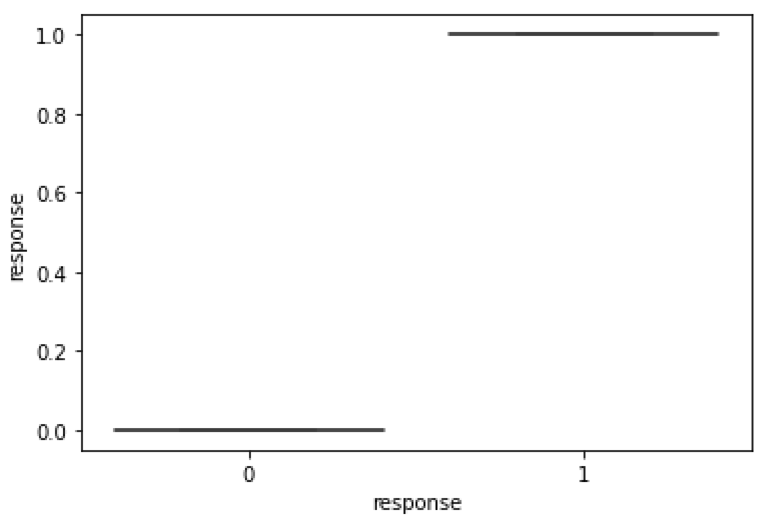

day
response
0
1
0
5
10
15
20
25
30


duration
response
0
1
0
500
1000
1500
2000


campaign
response
0
1
2
4
6
8
10
12
14
16


pdays
800
600
400
200
0
0
1
response


previous
250
200
150
100
50
0
0
1
response


response
1.0
0.8
0.6
0.4
0.2
0.0
0
1
response

In [37]:
```
df1[cat_cols]
```

Out[37]:

	targeted	month	contact	education	loan	job	poutcome	marital	housing	d
24060	yes	oct	telephone	tertiary	no	admin.	failure	married	no	
24062	yes	oct	telephone	secondary	yes	admin.	other	single	yes	
24064	yes	oct	telephone	secondary	no	services	failure	married	yes	
24072	yes	oct	telephone	tertiary	no	management	other	married	yes	
24077	yes	oct	telephone	tertiary	no	management	failure	married	yes	
...	...	...	...	...	...	...	...	...	...	
45199	yes	nov	cellular	secondary	no	blue-collar	other	single	yes	
45201	yes	nov	cellular	tertiary	no	management	success	married	no	
45204	yes	nov	cellular	secondary	no	retired	failure	married	no	
45208	yes	nov	cellular	secondary	no	retired	success	married	no	
45210	yes	nov	cellular	secondary	no	entrepreneur	other	married	no	

8257 rows × 10 columns

In [38]:
```
df1[cat_cols].nunique()
```

Out[38]:
```
targeted      2
month        12
contact       3
education     4
loan          2
job          12
poutcome      4
marital       3
housing       2
default       2
dtype: int64
```

In [39]:
```
df1[num_cols]
```

Out[39]:

	age	salary	balance	day	duration	campaign	pdays	previous	response
24060	33	50000	882	21	39	1	151	3	0
24062	42	50000	-247	21	519	1	166	1	1
24064	33	70000	3444	21	144	1	91	4	1
24072	36	100000	2415	22	73	1	86	4	0
24077	36	100000	0	23	140	1	143	3	1
...	...	...	...	...	...	...	...	...	...
45199	34	20000	1475	16	1166	3	530	12	0
45201	53	100000	583	17	226	1	184	4	1
45204	73	55000	2850	17	300	1	40	8	1
45208	72	55000	5715	17	1127	5	184	3	1
45210	37	120000	2971	17	361	2	188	11	0

8257 rows × 9 columns

In [40]:
```
##prprocessing
from sklearn.preprocessing import LabelEncoder
```

In [41]:
```
df_cat = df1[cat_cols].apply(LabelEncoder().fit_transform)
```

In [42]:
```
df_cat
```

Out[42]:

	targeted	month	contact	education	loan	job	poutcome	marital	housing	default
24060	1	10	1	2	0	0	0	1	0	0
24062	1	10	1	1	1	0	1	2	1	0
24064	1	10	1	1	0	7	0	1	1	0
24072	1	10	1	2	0	4	1	1	1	0
24077	1	10	1	2	0	4	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...
45199	1	9	0	1	0	1	1	2	1	0
45201	1	9	0	2	0	4	2	1	0	0
45204	1	9	0	1	0	5	0	1	0	0
45208	1	9	0	1	0	5	2	1	0	0
45210	1	9	0	1	0	2	1	1	0	0

8257 rows × 10 columns

In [43]:
```
dff = df_cat.join(df1[num_cols])
```

In [44]:
```
dff
```

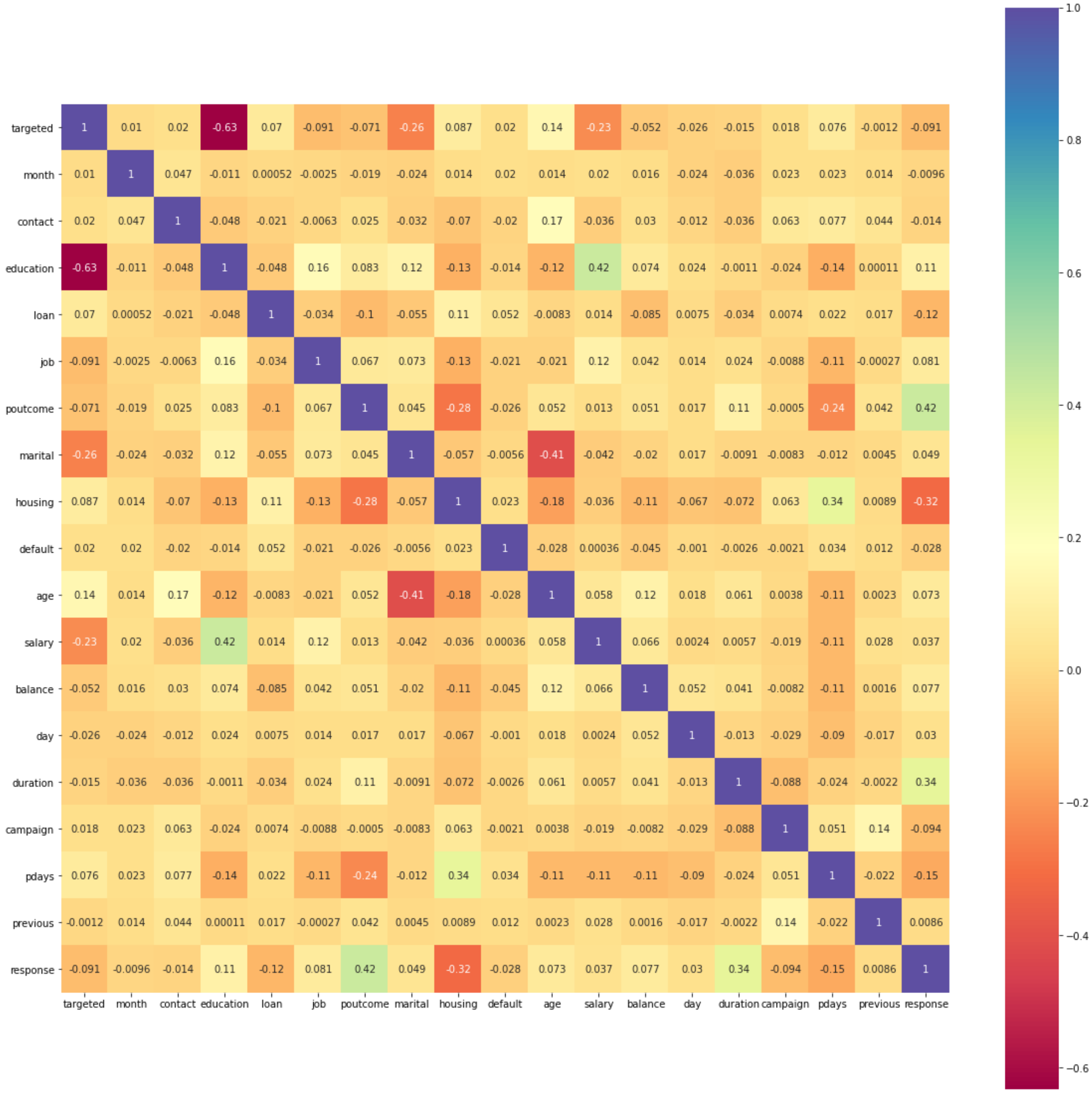
Out[44]:

	targeted	month	contact	education	loan	job	poutcome	marital	housing	default	age
24060	1	10	1	2	0	0	0	1	0	0	33
24062	1	10	1	1	1	0	1	2	1	0	42
24064	1	10	1	1	0	7	0	1	1	0	33
24072	1	10	1	2	0	4	1	1	1	0	36
24077	1	10	1	2	0	4	0	1	1	0	36
...	...	...	...	...	...	...	...	...	...	...	...
45199	1	9	0	1	0	1	1	2	1	0	34
45201	1	9	0	2	0	4	2	1	0	0	53
45204	1	9	0	1	0	5	0	1	0	0	73
45208	1	9	0	1	0	5	2	1	0	0	72
45210	1	9	0	1	0	2	1	1	0	0	37

8257 rows × 19 columns

In [45]:
```python
plt.figure(figsize=(20,20))
sns.heatmap(dff.corr(),square=True,annot=True,cmap= 'Spectral')
```

Out[45]: <AxesSubplot:>



In [46]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
import statsmodels.api as sm
from sklearn.metrics import accuracy_score
```

In [47]:
```python
##deviding data into independent and target variable
X = dff.drop('response',axis=1)
y = dff['response']
```

In [48]:
```
X.head()
```

Out[48]:

	targeted	month	contact	education	loan	job	poutcome	marital	housing	default	age
24060	1	10	1	2	0	0	0	1	0	0	33
24062	1	10	1	1	1	0	1	2	1	0	42
24064	1	10	1	1	0	7	0	1	1	0	33
24072	1	10	1	2	0	4	1	1	1	0	36
24077	1	10	1	2	0	4	0	1	1	0	36

In [49]:
```
y.head()
```

Out[49]:
```
24060    0
24062    1
24064    1
24072    0
24077    1
Name: response, dtype: int64
```

In [50]:
```
##splitting the data
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_stat
e=101)
```

In [51]:
```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[51]:
```
((5779, 18), (2478, 18), (5779,), (2478,))
```

In [52]:
```
lr = LogisticRegression(random_state=42)
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
```

In [53]:
```
print('Report:\n',classification_report(y_test, y_pred))
print("F1 Score:",f1_score(y_pred,y_test))
print('confusion Matrix:\n',confusion_matrix(y_pred,y_test))
print('cross validation:',cross_val_score(lr, X, y, cv=5))
```

```
Report:
               precision    recall  f1-score   support

           0       0.80      0.96      0.87      1915
           1       0.56      0.17      0.26       563

    accuracy                           0.78      2478
   macro avg       0.68      0.57      0.57      2478
weighted avg       0.74      0.78      0.73      2478

F1 Score: 0.2615803814713896
confusion Matrix:
 [[1840  467]
 [  75   96]]
cross validation: [0.79539952 0.72094431 0.77892187 0.7752877  0.75529982]
```

In [54]:
```
##using RFE feature selection
from sklearn.feature_selection import RFE
rfe = RFE(lr, n_features_to_select=10)
rfe.fit(X_train,y_train)
X_train_selected = rfe.transform(X_train)
X_train_selected.shape
```

Out[54]:
```
(5779, 10)
```

In [55]:
```
print(X_train.columns[rfe.support_])
cols = X_train.columns[rfe.support_]
lr.fit(X_train[cols],y_train)
y_pred2 = lr.predict(X_test[cols])
```

```
Index(['targeted', 'contact', 'education', 'loan', 'job', 'poutcome',
       'marital', 'housing', 'default', 'campaign'],
      dtype='object')
```

In [56]:
```
print('Report:\n',classification_report(y_test, y_pred2))
print("F1 Score:",f1_score(y_pred2,y_test))
print('AUC score:',roc_auc_score(y_test,y_pred2))
print('confusion Matrix:\n',confusion_matrix(y_pred2,y_test))
```

```
Report:
               precision    recall  f1-score   support

           0       0.84      0.95      0.89      1915
           1       0.71      0.38      0.49       563

    accuracy                           0.82      2478
   macro avg       0.77      0.67      0.69      2478
weighted avg       0.81      0.82      0.80      2478

F1 Score: 0.49479768786127165
AUC score: 0.6670767846625454
confusion Matrix:
 [[1827  349]
 [  88  214]]
```

In [57]:
```
import statsmodels.api as sm
model = sm.OLS(y, X)
results = model.fit()
start = "\033[1m" ### for bold text
print(start)
print(results.summary())
```

```
                             OLS Regression Results
==============================================================================
==========
Dep. Variable:               response   R-squared (uncentered):
0.473
Model:                            OLS   Adj. R-squared (uncentered):
0.471
Method:                 Least Squares   F-statistic:
410.2
Date:                Sun, 07 Mar 2021   Prob (F-statistic):
0.00
Time:                        10:01:37   Log-Likelihood:
-3019.6
No. Observations:                8257   AIC:
6075.
Df Residuals:                    8239   BIC:
6202.
Df Model:                          18
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
targeted      -0.0097      0.011     -0.888      0.375      -0.031       0.01
2
month          0.0016      0.001      1.490      0.136      -0.001       0.00
4
contact       -0.0346      0.012     -2.794      0.005      -0.059      -0.01
0
education      0.0263      0.007      3.946      0.000       0.013       0.03
9
loan          -0.0561      0.011     -4.924      0.000      -0.078      -0.03
4
job            0.0023      0.001      1.885      0.059   -9.01e-05       0.00
5
poutcome       0.1764      0.005     33.992      0.000       0.166       0.18
7
marital        0.0176      0.006      2.952      0.003       0.006       0.02
9
housing       -0.1598      0.009    -18.442      0.000      -0.177      -0.14
3
default       -0.0571      0.047     -1.225      0.220      -0.148       0.03
4
age            0.0010      0.000      3.218      0.001       0.000       0.00
2
salary     -5.745e-09   1.35e-07     -0.042      0.966   -2.71e-07    2.59e-0
7
balance     2.489e-06   1.28e-06      1.940      0.052   -2.55e-08      5e-0
6
day            0.0007      0.000      1.449      0.147      -0.000       0.00
2
duration       0.0005   1.65e-05     31.037      0.000       0.000       0.00
1
campaign      -0.0148      0.002     -5.954      0.000      -0.020      -0.01
```

```
0
pdays        5.526e-05    3.5e-05      1.578      0.115   -1.34e-05       0.00
0
previous        0.0007      0.001      0.765      0.444      -0.001       0.00
2
==============================================================================
=
Omnibus:                      581.061   Durbin-Watson:                   1.79
2
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              709.92
4
Skew:                           0.692   Prob(JB):                   6.95e-15
5
Kurtosis:                       3.383   Cond. No.                    7.97e+0
5
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 7.97e+05. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [58]:
```
##from above summery we can say that some of features are higher p value,so le
ts check vifs
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in range(X_tr
ain.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[58]:

	Features	VIF
10	age	11.66
0	targeted	6.44
3	education	6.38
11	salary	5.36
16	pdays	5.23
7	marital	4.37
13	day	4.07
1	month	3.56
8	housing	3.13
5	job	2.92
15	campaign	2.75
14	duration	2.28
6	poutcome	1.76
17	previous	1.45
12	balance	1.31
4	loan	1.20
2	contact	1.15
9	default	1.02

In [59]:
```
from sklearn.feature_selection import SelectFromModel
smf = SelectFromModel(lr)
smf.fit(X_train,y_train)
features = smf.get_support()
feature_name = X_train.columns[features]
feature_name
```

Out[59]:
```
Index(['month', 'poutcome', 'housing', 'day', 'campaign', 'previous'], dtype
='object')
```

In [60]:
```
X_cols =X.loc[:,['housing', 'month', 'poutcome', 'day','campaign', 'previous'
]]
```

In [61]:
```
X_cols
```

Out[61]:

	housing	month	poutcome	day	campaign	previous
24060	0	10	0	21	1	3
24062	1	10	1	21	1	1
24064	1	10	0	21	1	4
24072	1	10	1	22	1	4
24077	1	10	0	23	1	3
...	...	...	...	...	...	...
45199	1	9	1	16	3	12
45201	0	9	2	17	1	4
45204	0	9	0	17	1	8
45208	0	9	2	17	5	3
45210	0	9	1	17	2	11

8257 rows × 6 columns

In [62]:
```
cross_val_score(lr,X_cols,y)
```

Out[62]:
```
array([0.75121065, 0.84200969, 0.86553604, 0.84736523, 0.66989703])
```

In [63]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [64]:
```
rfc = RandomForestClassifier(n_estimators=20,max_depth=5,criterion='entropy',n
_jobs=1,random_state=101)
```

In [65]:
```
rfc.fit(X_train,y_train)
```

Out[65]:
```
RandomForestClassifier(criterion='entropy', max_depth=5, n_estimators=20,
                       n_jobs=1, random_state=101)
```

In [66]:
```
y_pred1 = rfc.predict(X_test)
```

In [67]:
```
print('Report:\n',classification_report(y_test, y_pred1))
print("F1 Score:",f1_score(y_pred1,y_test))
print('confusion Matrix:\n',confusion_matrix(y_pred1,y_test))
```

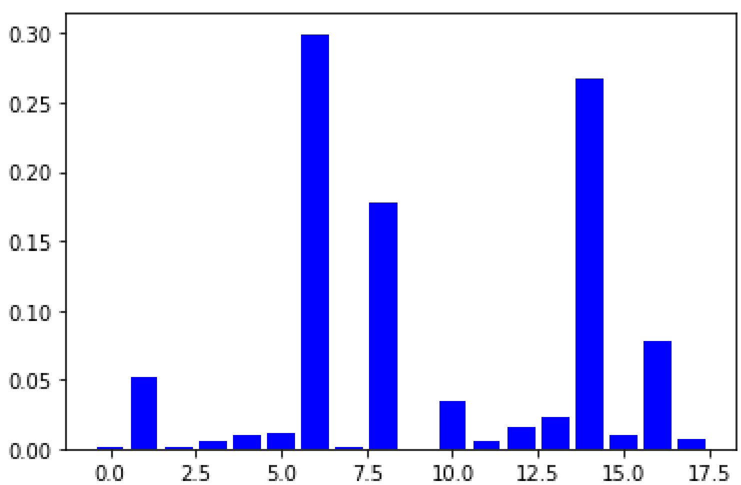
```
Report:
               precision    recall  f1-score   support

           0       0.84      0.97      0.90      1915
           1       0.79      0.39      0.52       563

    accuracy                           0.84      2478
   macro avg       0.82      0.68      0.71      2478
weighted avg       0.83      0.84      0.82      2478

F1 Score: 0.5249406175771972
confusion Matrix:
 [[1857  342]
 [  58  221]]
```

In [68]:
```
cross_val_score(rfc,X,y)
```

Out[68]:
```
array([0.77602906, 0.81840194, 0.85342217, 0.85342217, 0.59539673])
```

In [69]:
```
features=rfc.feature_importances_
```

In [70]:
```
plt.bar(range(X_train.shape[1]),features,color='blue')
plt.show()
```



In [71]:
```
imp_df = dff.iloc[:,[2,4,5,14,16]]
```

In [72]:
```
imp_df
```

Out[72]:

	contact	loan	job	duration	pdays
24060	1	0	0	39	151
24062	1	1	0	519	166
24064	1	0	7	144	91
24072	1	0	4	73	86
24077	1	0	4	140	143
...	...	...	...	...	...
45199	0	0	1	1166	530
45201	0	0	4	226	184
45204	0	0	5	300	40
45208	0	0	5	1127	184
45210	0	0	2	361	188

8257 rows × 5 columns

In [73]:
```
y
```

Out[73]:
```
24060    0
24062    1
24064    1
24072    0
24077    1
        ..
45199    0
45201    1
45204    1
45208    1
45210    0
Name: response, Length: 8257, dtype: int64
```

In [74]:
```
x_train,x_test,y_train,y_test = train_test_split(imp_df,y,test_size=0.2,random
_state=0)
```

In [75]:
```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[75]:
```
((6605, 5), (1652, 5), (6605,), (1652,))
```

In [76]:
```
##logistic regression with imp features
logreg=LogisticRegression(random_state=0)
```

In [77]:
```
logreg.fit(x_train,y_train)
```

Out[77]:
```
LogisticRegression(random_state=0)
```

In [78]:
```
y_predf = logreg.predict(x_test)
```

In [79]:
```
def LR():
    print('Report:\n',classification_report(y_test, y_predf))
    print("F1 Score:",f1_score(y_test,y_predf))
    print('confusion Matrix:\n',confusion_matrix(y_test,y_predf))
```

In [80]:
```
LR()
```

```
Report:
               precision    recall  f1-score   support

           0       0.79      0.96      0.87      1255
           1       0.61      0.20      0.31       397

    accuracy                           0.78      1652
   macro avg       0.70      0.58      0.59      1652
weighted avg       0.75      0.78      0.73      1652

F1 Score: 0.3056603773584906
confusion Matrix:
 [[1203   52]
 [ 316   81]]
```

In [81]:
```
rfcf = RandomForestClassifier(criterion='gini',n_estimators=40,n_jobs=1,max_de
pth=5,random_state=0)
```

In [82]:
```
rfcf.fit(x_train,y_train)
```

Out[82]:
```
RandomForestClassifier(max_depth=5, n_estimators=40, n_jobs=1, random_state=
0)
```

In [83]:
```
y_predicf=rfcf.predict(x_test)
```

In [84]:
```
def RFC():
    print('Report:\n',classification_report(y_test, y_predicf))
    print("F1 Score:",f1_score(y_test,y_predicf))
    print('confusion Matrix:\n',confusion_matrix(y_test,y_predicf))
```

In [85]:
```
RFC()
```

```
Report:
               precision    recall  f1-score   support

           0       0.81      0.95      0.87      1255
           1       0.64      0.29      0.40       397

    accuracy                           0.79      1652
   macro avg       0.72      0.62      0.64      1652
weighted avg       0.77      0.79      0.76      1652

F1 Score: 0.40138408304498274
confusion Matrix:
 [[1190   65]
 [ 281  116]]
```

If we compare both models that is logisticregression an random forest classifier ,the scores of both models little bit different after train with important featuers both doing good not very good but its okay and i didnt normalize the numerical features if we normalize or standerdize the numeric cols the accuracy will increase.

Thank you BoardInfinity and Thanks to punith sir

In [ ]:

```

```

In [ ]:

```
###without dropping pdays -1 values
```

In [97]:

```
df.head()
```

Out[97]:

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

In [ ]:

```
#Pdays: number of days that passed by after the client was last
#contacted from a previous campaign (numeric; 999 means client was not
#previously contacted)
```

In [98]:

```
df['pdays'].replace(-1,999,inplace=True)
```

In [101]:

```
df.head()
```

Out[101]:

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

In [105]:
```
labelencoder_X = LabelEncoder()
df['job']       = labelencoder_X.fit_transform(df['job'])
df['marital']   = labelencoder_X.fit_transform(df['marital'])
df['education']= labelencoder_X.fit_transform(df['education'])
df['targeted'] = labelencoder_X.fit_transform(df['targeted'])
df['default']   = labelencoder_X.fit_transform(df['default'])
df['housing']   = labelencoder_X.fit_transform(df['housing'])
df['loan']      = labelencoder_X.fit_transform(df['loan'])
df['contact']      = labelencoder_X.fit_transform(df['contact'])
df['month']        = labelencoder_X.fit_transform(df['month'])
df['poutcome'] = labelencoder_X.fit_transform(df['poutcome'])
df['response'] = labelencoder_X.fit_transform(df['response'])
```

In [106]:
```
df.head()
```

Out[106]:

	age	job	salary	marital	education	targeted	default	balance	housing	loan	contact	day
0	58	4	100000	1	2	1	0	2143	1	0	2	5
1	44	9	60000	2	1	1	0	29	1	0	2	5
2	33	2	120000	1	1	1	0	2	1	1	2	5
3	47	1	20000	1	3	0	0	1506	1	0	2	5
4	33	11	0	2	3	0	0	1	0	0	2	5

In [108]:
```
df.shape
```

Out[108]: (45211, 19)

In [115]:
```
X=df.drop('response',axis=1)
y=df['response']
```

In [116]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, ra
ndom_state = 101)

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

In [117]:
```
X_train.head()
```

Out[117]:

	age	job	salary	marital	education	targeted	default	balance	housing	loan	contact
3734	26	1	20000	2	0	1	0	102	1	0	2
28119	43	4	100000	1	2	1	0	182	0	0	0
36942	37	9	60000	1	1	1	0	807	1	0	0
4710	32	1	20000	1	0	1	0	80	1	0	2
26402	33	2	120000	1	2	1	0	0	0	0	0

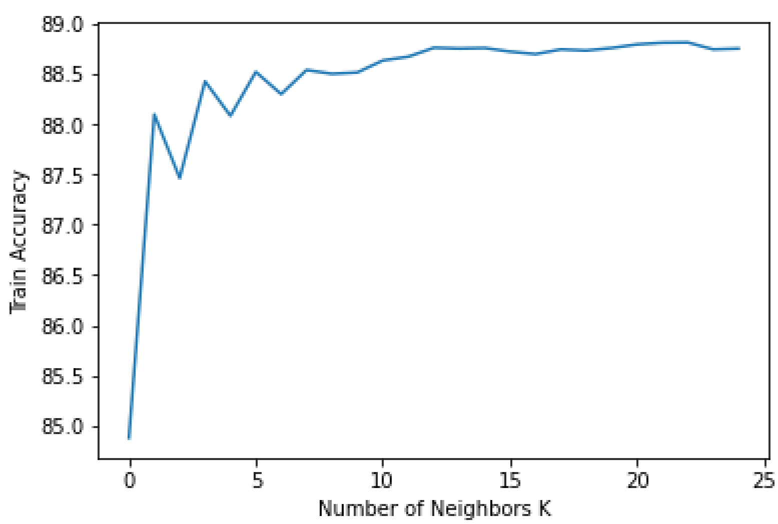
In [118]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

In [119]:
```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)


print(confusion_matrix(y_test, logpred))
print(round(accuracy_score(y_test, logpred),2)*100)
LOGCV = (cross_val_score(logmodel, X_train, y_train, cv=k_fold, n_jobs=1, scor
ing = 'accuracy').mean())
```

```
[[7787  157]
 [ 748  351]]
90.0
```

In [120]:
```
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier

X_trainK, X_testK, y_trainK, y_testK = train_test_split(X, y, test_size = 0.2,
random_state = 101)

#Neighbors
neighbors = np.arange(0,25)

#Create empty list that will hold cv scores
cv_scores = []

#Perform 10-fold cross validation on training set for odd values of k:
for k in neighbors:
    k_value = k+1
    knn = KNeighborsClassifier(n_neighbors = k_value, weights='uniform', p=2,
metric='euclidean')
    kfold = model_selection.KFold(n_splits=10, random_state=123)
    scores = model_selection.cross_val_score(knn, X_trainK, y_trainK, cv=kfold
, scoring='accuracy')
    cv_scores.append(scores.mean()*100)
    print("k=%d %0.2f (+/- %0.2f)" % (k_value, scores.mean()*100, scores.std()
*100))

optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print ("The optimal number of neighbors is %d with %0.1f%%" % (optimal_k, cv_s
cores[optimal_k]))

plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Train Accuracy')
plt.show()
```

```
k=1 84.88 (+/- 0.56)
k=2 88.09 (+/- 0.52)
k=3 87.46 (+/- 0.61)
k=4 88.42 (+/- 0.57)
k=5 88.08 (+/- 0.57)
k=6 88.52 (+/- 0.44)
k=7 88.30 (+/- 0.60)
k=8 88.54 (+/- 0.44)
k=9 88.50 (+/- 0.50)
k=10 88.51 (+/- 0.46)
k=11 88.63 (+/- 0.50)
k=12 88.67 (+/- 0.46)
k=13 88.76 (+/- 0.50)
k=14 88.75 (+/- 0.54)
k=15 88.76 (+/- 0.51)
k=16 88.72 (+/- 0.51)
k=17 88.69 (+/- 0.54)
k=18 88.74 (+/- 0.58)
k=19 88.73 (+/- 0.53)
k=20 88.76 (+/- 0.57)
k=21 88.79 (+/- 0.52)
k=22 88.81 (+/- 0.63)
k=23 88.81 (+/- 0.54)
k=24 88.74 (+/- 0.54)
k=25 88.75 (+/- 0.52)
The optimal number of neighbors is 22 with 88.8%
```



In [121]:
```
knn = KNeighborsClassifier(n_neighbors=22)
knn.fit(X_train, y_train)
knnpred = knn.predict(X_test)

print(confusion_matrix(y_test, knnpred))
print(round(accuracy_score(y_test, knnpred),2)*100)
KNNCV = (cross_val_score(knn, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())
```

```
[[7838  106]
 [ 860  239]]
89.0
```

In [122]:
```
from sklearn.svm import SVC
svc= SVC(kernel = 'sigmoid')
svc.fit(X_train, y_train)
svcpred = svc.predict(X_test)
print(confusion_matrix(y_test, svcpred))
print(round(accuracy_score(y_test, svcpred),2)*100)
SVCCV = (cross_val_score(svc, X_train, y_train, cv=k_fold, n_jobs=1, scoring =
'accuracy').mean())
```

```
[[7299  645]
 [ 760  339]]
84.0
```

In [123]:
```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(criterion='gini') #criterion = entopy, gini
dtree.fit(X_train, y_train)
dtreepred = dtree.predict(X_test)

print(confusion_matrix(y_test, dtreepred))
print(round(accuracy_score(y_test, dtreepred),2)*100)
DTREECV = (cross_val_score(dtree, X_train, y_train, cv=k_fold, n_jobs=1, scori
ng = 'accuracy').mean())
```

```
[[7372  572]
 [ 566  533]]
87.0
```

In [124]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 200)#criterion = entopy,gini
rfc.fit(X_train, y_train)
rfcpred = rfc.predict(X_test)

print(confusion_matrix(y_test, rfcpred ))
print(round(accuracy_score(y_test, rfcpred),2)*100)
RFCCV = (cross_val_score(rfc, X_train, y_train, cv=k_fold, n_jobs=1, scoring =
'accuracy').mean())
```

```
[[7753  191]
 [ 657  442]]
91.0
```

In [125]:
```
from sklearn.naive_bayes import GaussianNB
gaussiannb= GaussianNB()
gaussiannb.fit(X_train, y_train)
gaussiannbpred = gaussiannb.predict(X_test)
probs = gaussiannb.predict(X_test)

print(confusion_matrix(y_test, gaussiannbpred ))
print(round(accuracy_score(y_test, gaussiannbpred),2)*100)
GAUSIAN = (cross_val_score(gaussiannb, X_train, y_train, cv=k_fold, n_jobs=1,
scoring = 'accuracy').mean())
```

```
[[6958  986]
 [ 478  621]]
84.0
```

In [126]:
```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
xgbprd = xgb.predict(X_test)

print(confusion_matrix(y_test, xgbprd ))
print(round(accuracy_score(y_test, xgbprd),2)*100)
XGB = (cross_val_score(estimator = xgb, X = X_train, y = y_train, cv = 10).mea
n())
```

```
[[7668  276]
 [ 565  534]]
91.0
```

In [127]:
```
from sklearn.ensemble import GradientBoostingClassifier
gbk = GradientBoostingClassifier()
gbk.fit(X_train, y_train)
gbkpred = gbk.predict(X_test)
print(confusion_matrix(y_test, gbkpred ))
print(round(accuracy_score(y_test, gbkpred),2)*100)
GBKCV = (cross_val_score(gbk, X_train, y_train, cv=k_fold, n_jobs=1, scoring =
'accuracy').mean())
```

```
[[7756  188]
 [ 654  445]]
91.0
```

In [128]:
```
models = pd.DataFrame({
                'Models': ['Random Forest Classifier', 'Decision Tree Classifi
er', 'Support Vector Machine',
                           'K-Near Neighbors', 'Logistic Model', 'Gausian NB',
'XGBoost', 'Gradient Boosting'],
                'Score':  [RFCCV, DTREECV, SVCCV, KNNCV, LOGCV, GAUSIAN, XGB,
GBKCV]})

models.sort_values(by='Score', ascending=False)
```

Out[128]:

	Models	Score
6	XGBoost	0.908206
0	Random Forest Classifier	0.903893
7	Gradient Boosting	0.903284
4	Logistic Model	0.898612
3	K-Near Neighbors	0.894962
1	Decision Tree Classifier	0.872374
2	Support Vector Machine	0.844531
5	Gausian NB	0.836292

In [ ]: