Ensemble techniques -Project3 - Edouard Toutounji - 21 Feb 2020

October 27, 2025

1 1- Exploratory data analysis of the 'bank-full.csv' data as is - prior to any changes

1.1 1.1. Non visual analysis

Comments will follow to set a path on how to make necesseary changes that will be implemented in part 2

[254]:
```
# importing EDA librabries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

[255]:
```
# loading the data into the dataframe TDS ( Term Deposit Sale)
TDS = pd.read_csv('bank-full.csv')
```

[256]:
```
TDS.head(100)

# first impression : many of the 16 attributes are categorical
# and will require transformation to ordinal level or using dummy variables.
```

[256]:
```
    age          job  marital  education default  balance housing loan  \
0    58   management  married   tertiary      no     2143     yes   no
1    44   technician   single  secondary      no       29     yes   no
2    33 entrepreneur  married  secondary      no        2     yes  yes
3    47  blue-collar  married    unknown      no     1506     yes   no
4    33      unknown   single    unknown      no        1      no   no
..  …            …        …          …     …        …      …   …
95   36   management  married   tertiary      no      101     yes  yes
96   55  blue-collar  married  secondary      no      383      no   no
97   60      retired  married   tertiary      no       81     yes   no
98   39   technician  married  secondary      no        0     yes   no
99   46   management  married   tertiary      no      229     yes   no

    contact  day month  duration  campaign  pdays  previous poutcome Target
0   unknown    5   may       261         1     -1         0  unknown     no
```

```
1    unknown    5   may       151          1     -1          0  unknown     no
2    unknown    5   may        76          1     -1          0  unknown     no
3    unknown    5   may        92          1     -1          0  unknown     no
4    unknown    5   may       198          1     -1          0  unknown     no
..       …   …   …       …        …     …        …       …      …
95   unknown    5   may       426          1     -1          0  unknown     no
96   unknown    5   may       287          1     -1          0  unknown     no
97   unknown    5   may       101          1     -1          0  unknown     no
98   unknown    5   may       203          1     -1          0  unknown     no
99   unknown    5   may       197          1     -1          0  unknown     no

[100 rows x 17 columns]
```

[257]:
```
# column names
TDS.columns
```

[257]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'Target'],
      dtype='object')
```

[258]:
```
# data size and shape
TDS.shape
```

[258]:
```
(45211, 17)
```

[259]:
```
# dtypes of the attributes columns
TDS.dtypes

# confirmation that many attributes are of type: 'object' --> to be transformed
↪later
```

[259]:
```
age           int64
job          object
marital      object
education    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
Target       object
dtype: object
```

[260]:
```
TDS.info()
# NO missing values however some surprises could be expected that may require
↪replacement(s) later on.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
age          45211 non-null int64
job          45211 non-null object
marital      45211 non-null object
education    45211 non-null object
default      45211 non-null object
balance      45211 non-null int64
housing      45211 non-null object
loan         45211 non-null object
contact      45211 non-null object
day          45211 non-null int64
month        45211 non-null object
duration     45211 non-null int64
campaign     45211 non-null int64
pdays        45211 non-null int64
previous     45211 non-null int64
poutcome     45211 non-null object
Target       45211 non-null object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

[261]:
```
# statistical analysis of the numerical attributes
TDS.describe().transpose()

# attributes where [ mean is quite > than median ] is an indicator of strong
↪right skewness;
# and presence of outliers in the respective distributions is also confirmed by
↪the (max/min) values.

# this is observed for : 'balance' , 'duration' , 'campaign', 'pdays',
↪'previous'
```

[261]:
```
            count         mean          std     min    25%    50%     75%  \
age       45211.0    40.936210    10.618762    18.0   33.0   39.0    48.0
balance   45211.0  1362.272058  3044.765829 -8019.0   72.0  448.0  1428.0
day       45211.0    15.806419     8.322476     1.0    8.0   16.0    21.0
duration  45211.0   258.163080   257.527812     0.0  103.0  180.0   319.0
```

```
campaign  45211.0     2.763841     3.098021     1.0     1.0     2.0     3.0
pdays     45211.0    40.197828   100.128746    -1.0    -1.0    -1.0    -1.0
previous  45211.0     0.580323     2.303441     0.0     0.0     0.0     0.0

               max
age           95.0
balance   102127.0
day           31.0
duration    4918.0
campaign      63.0
pdays        871.0
previous     275.0
```

[262]:

```python
# confirming our hunch about the data by printing the values counts of all␣
↪columns/attributes.

for column in TDS.columns:
    print(TDS[column].value_counts(), '\n')
```

```
32    2085
31    1996
33    1972
34    1930
35    1894
      …
90       2
92       2
93       2
95       2
94       1
Name: age, Length: 77, dtype: int64

blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64

married     27214
single      12790
```

```
divorced     5207
Name: marital, dtype: int64

secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64

no     44396
yes      815
Name: default, dtype: int64

0        3514
1         195
2         156
4         139
3         134
         …
4305        1
6352        1
18881       1
14889       1
7218        1
Name: balance, Length: 7168, 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

20    2752
18    2308
21    2026
17    1939
6     1932
5     1910
14    1848
8     1842
28    1830
```

```
7     1817
19    1757
29    1745
15    1703
12    1603
13    1585
30    1566
9     1561
11    1479
4     1445
16    1415
2     1293
27    1121
3     1079
26    1035
23     939
22     905
25     840
31     643
10     524
24     447
1      322
Name: day, 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

124     188
90      184
89      177
122     175
104     175
       …
2150      1
1970      1
1906      1
1842      1
```

```
2015      1
Name: duration, Length: 1573, dtype: int64

1     17544
2     12505
3      5521
4      3522
5      1764
6      1291
7       735
8       540
9       327
10      266
11      201
12      155
13      133
14       93
15       84
16       79
17       69
18       51
19       44
20       43
21       35
22       23
23       22
25       22
24       20
28       16
29       16
26       13
31       12
27       10
32        9
30        8
33        6
34        5
36        4
35        4
43        3
38        3
41        2
50        2
37        2
51        1
55        1
46        1
58        1
```

```
44        1
39        1
63        1
Name: campaign, dtype: int64

-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

0      36954
1       2772
2       2106
3       1142
4        714
5        459
6        277
7        205
8        129
9         92
10        67
11        65
12        44
13        38
15        20
14        19
17        15
16        13
19        11
23         8
20         8
22         6
18         6
24         5
27         5
29         4
25         4
21         4
30         3
28         2
```

```
26        2
37        2
38        2
55        1
40        1
35        1
58        1
51        1
41        1
32        1
275       1
Name: previous, dtype: int64

unknown    36959
failure     4901
other       1840
success     1511
Name: poutcome, dtype: int64

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

Before jumping to graphical univariate analysis , some important peliminary observations on the distributions of some attributes.

1 - 'Target' : is tilted largely towards 'no'. (so the chances of guessing by chance are not 50 - 50)

2 - 'poutcome': shows that clients labeled as 'unknown' are = 36959

3 - 'pdays' : shows that clients labeled as '-1' = 36954

This seems to confirm that previously uncontacted clients amoun to approx. 36950.

4 - 'previous': shows strong right skweness and an outlier '275'

5 - 'campaign': shows strong right skewness and an outlier '63'

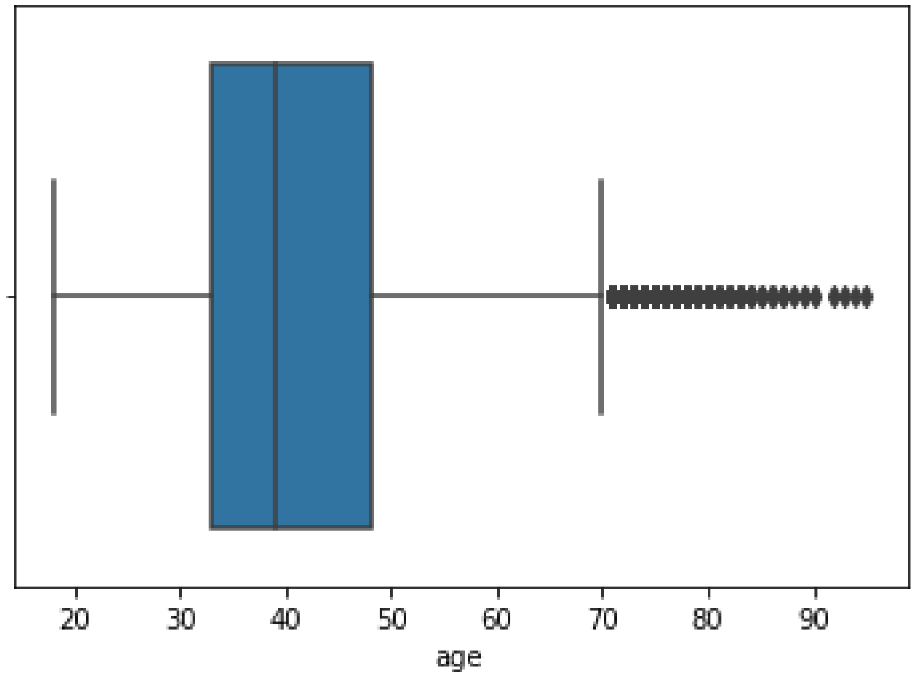
1.2 1.2. Univariate Graphical analysis column by column.

[263]:
```
TDS.columns
```

[263]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'Target'],
      dtype='object')
```

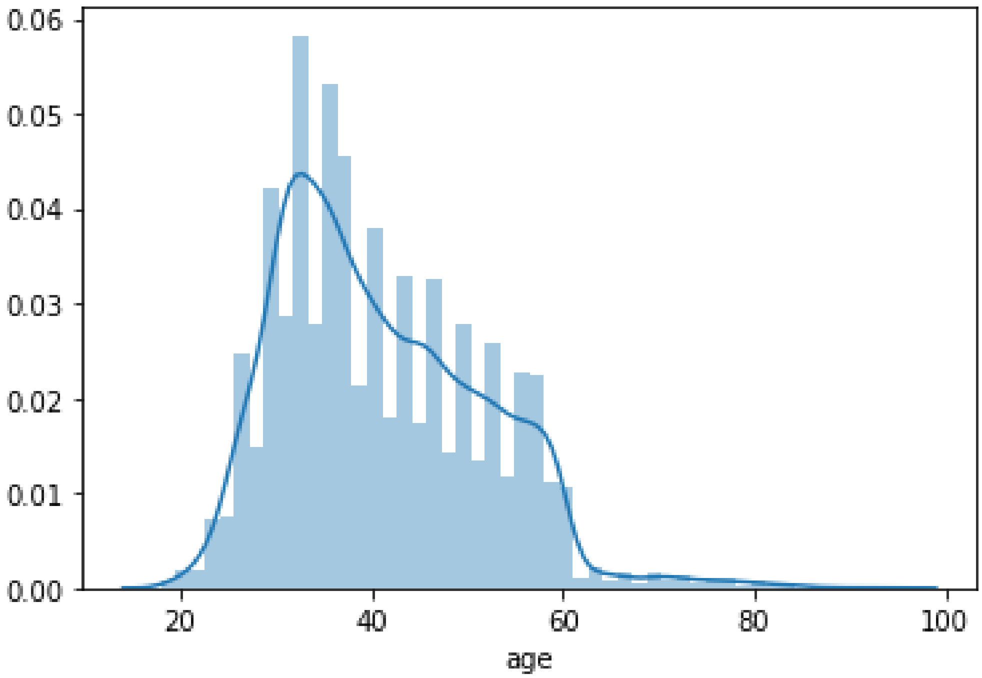
[264]:
```
# plotting the distributions of All 17 columns.

sns.boxplot(TDS.age)
```

[264]: <matplotlib.axes._subplots.AxesSubplot at 0x1a43724090>



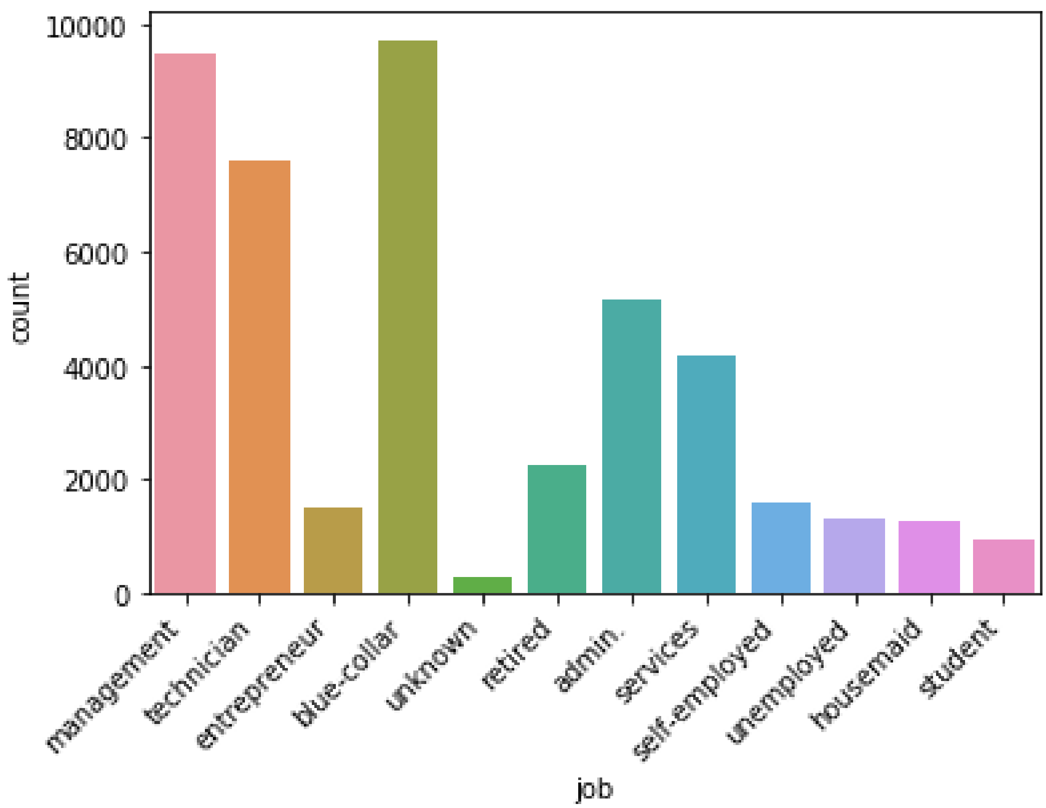
[265]:
```
sns.distplot(TDS.age)
# boxplot for 'age' - a big drop after 60.
```

[265]: <matplotlib.axes._subplots.AxesSubplot at 0x1a44511390>



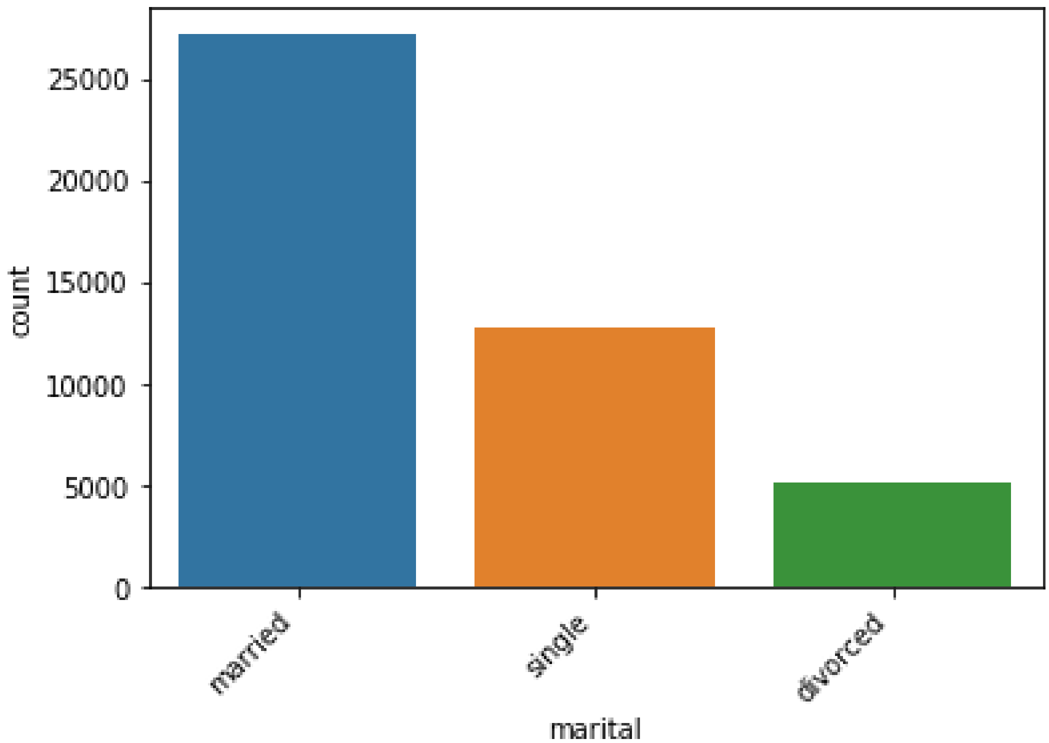
[266]:
```
sns.countplot(TDS.job)
plt.xticks(rotation=45, horizontalalignment='right')

# 'unknown' category could be dropped as it gives no insight into classifying␣
 ↪clients and is minimal in count.
TDS.job.value_counts()
```

[266]:
```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```



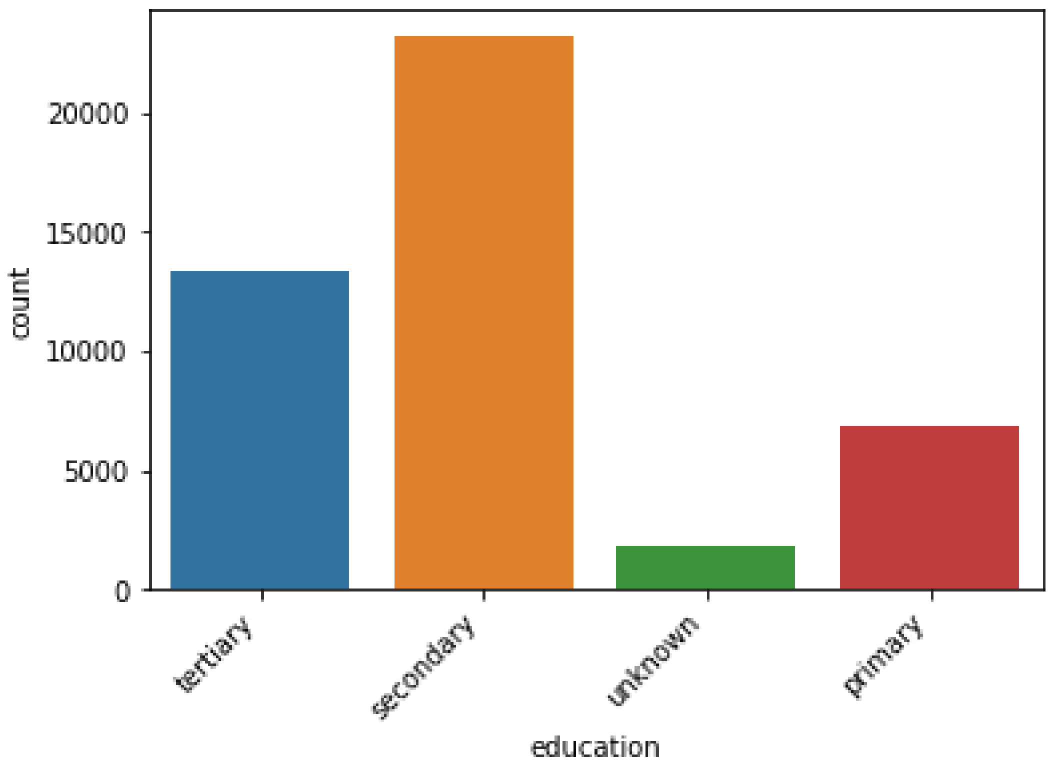
[267]:
```
sns.countplot(TDS.marital)
plt.xticks(rotation=45, horizontalalignment='right')

# majority of our pool are 'married'
TDS.marital.value_counts()
```

[267]:
```
married     27214
single      12790
divorced     5207
Name: marital, dtype: int64
```



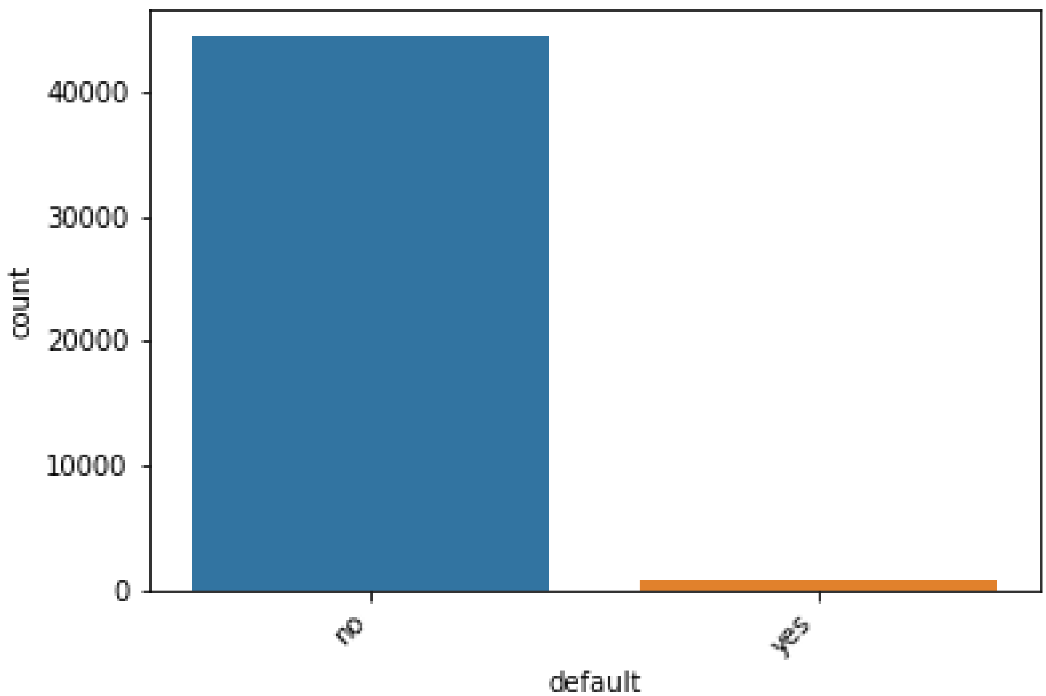
[268]:
```
sns.countplot(TDS.education)
plt.xticks(rotation=45, horizontalalignment='right')

# 'unknown' education label is a flag for later analysis
TDS.education.value_counts()
```

[268]:
```
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64
```



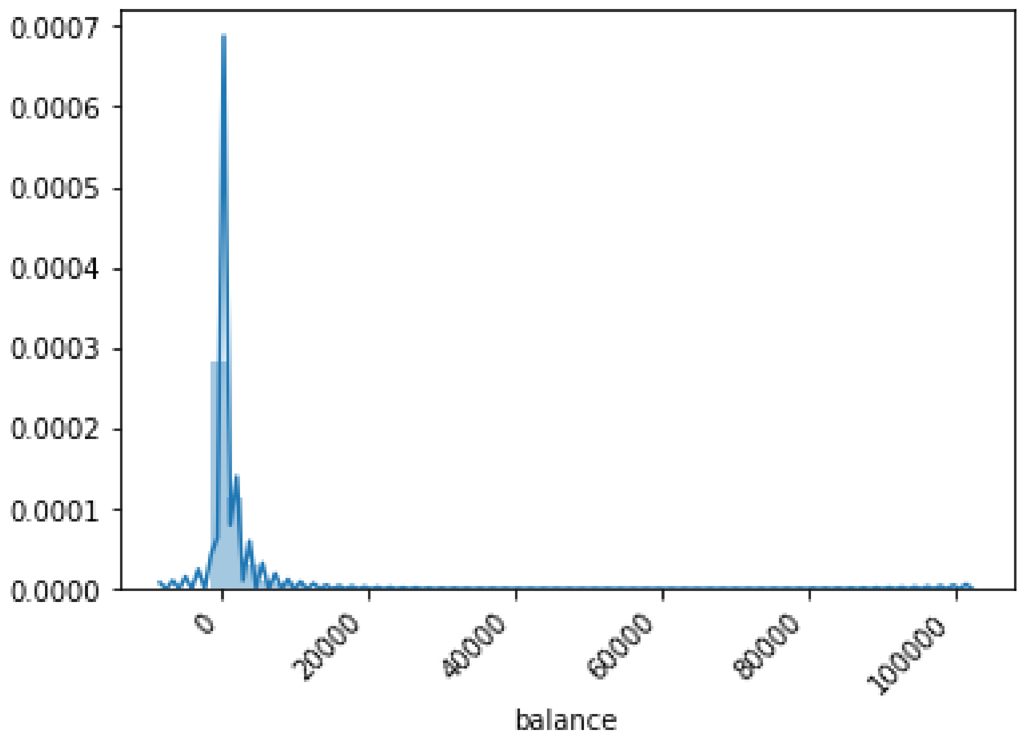
[269]:
```
sns.countplot(TDS.default)
plt.xticks(rotation=45, horizontalalignment='right')

# imbalance : the Big majority have not defaulted. There are no unknowns.
TDS.default.value_counts()
```

[269]:
```
no     44396
yes      815
Name: default, dtype: int64
```



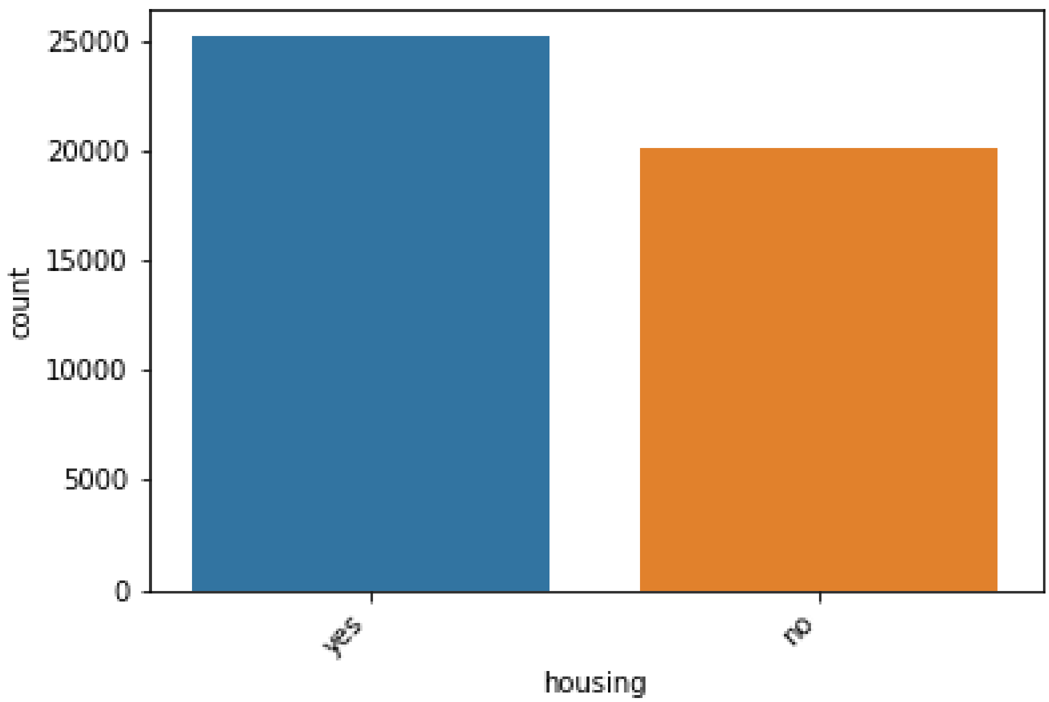
[270]:
```
sns.distplot(TDS.balance)
plt.xticks(rotation=45, horizontalalignment='right')

# outliers could be those clients with balance above 20,000.
```

[270]:
```
(array([-20000.,      0.,  20000.,  40000.,  60000.,  80000., 100000.,
        120000.]), <a list of 8 Text xticklabel objects>)
```



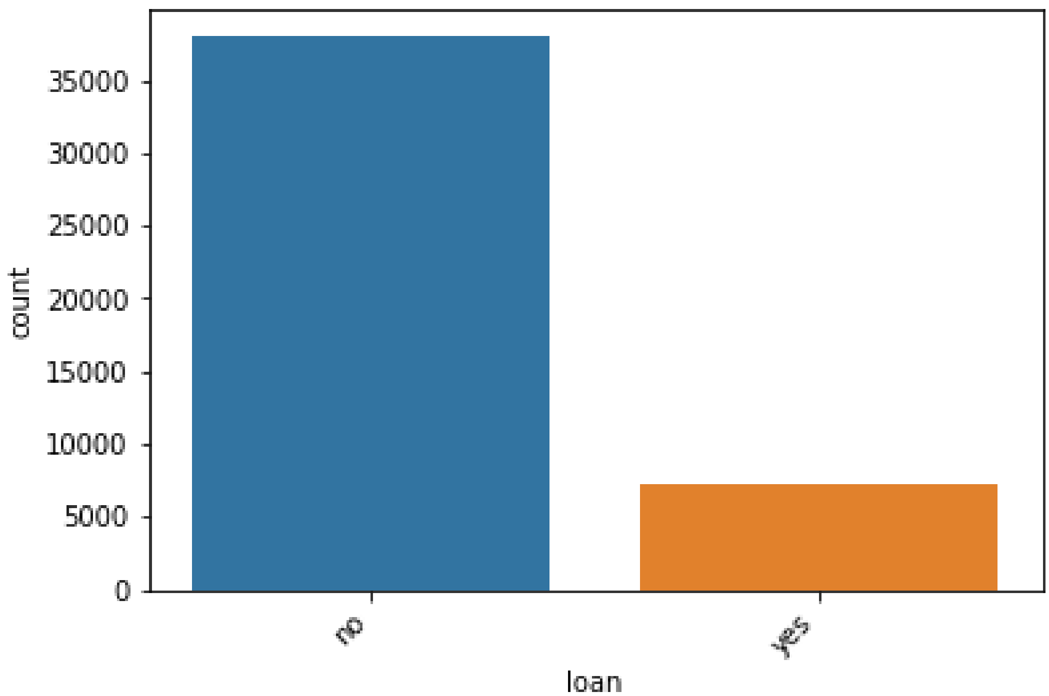
[271]:
```
sns.countplot(TDS.housing)
plt.xticks(rotation=45, horizontalalignment='right')

# no strong influence expected from housing loans as it is roughly balanced in
 ↪our pool
TDS.housing.value_counts()
```

[271]:
```
yes    25130
no     20081
Name: housing, dtype: int64
```



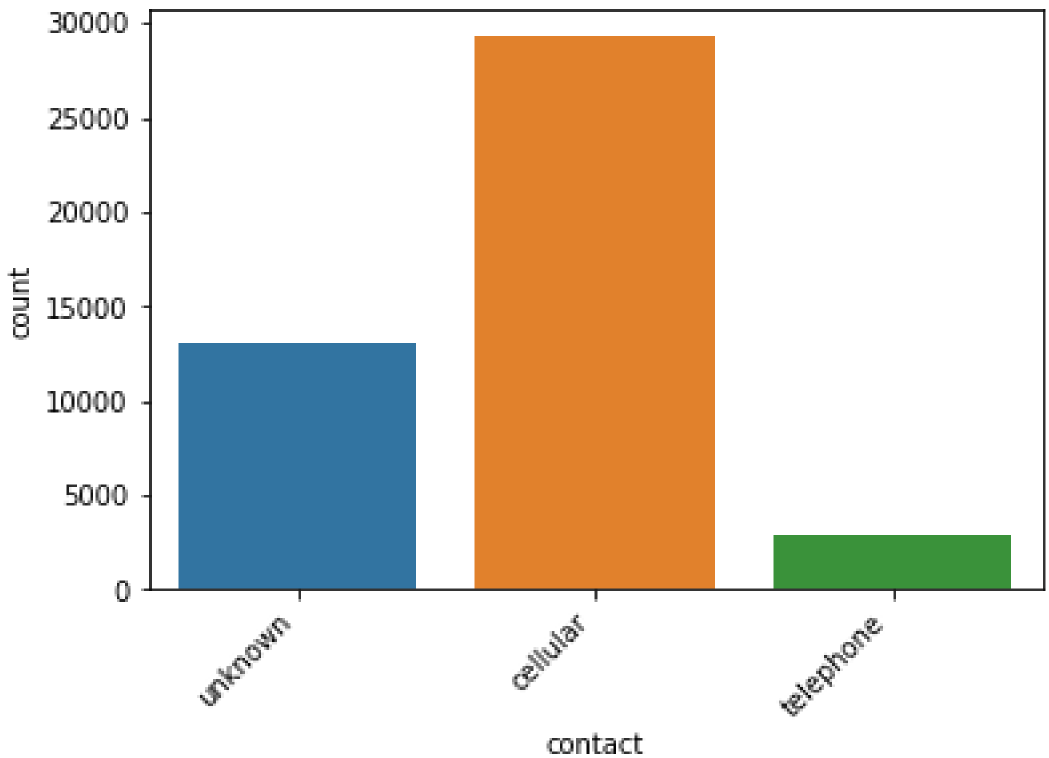
[272]:
```
sns.countplot(TDS.loan)
plt.xticks(rotation=45, horizontalalignment='right')

# Majority do not have personal loans
TDS.loan.value_counts()
```

[272]:
```
no      37967
yes      7244
Name: loan, dtype: int64
```



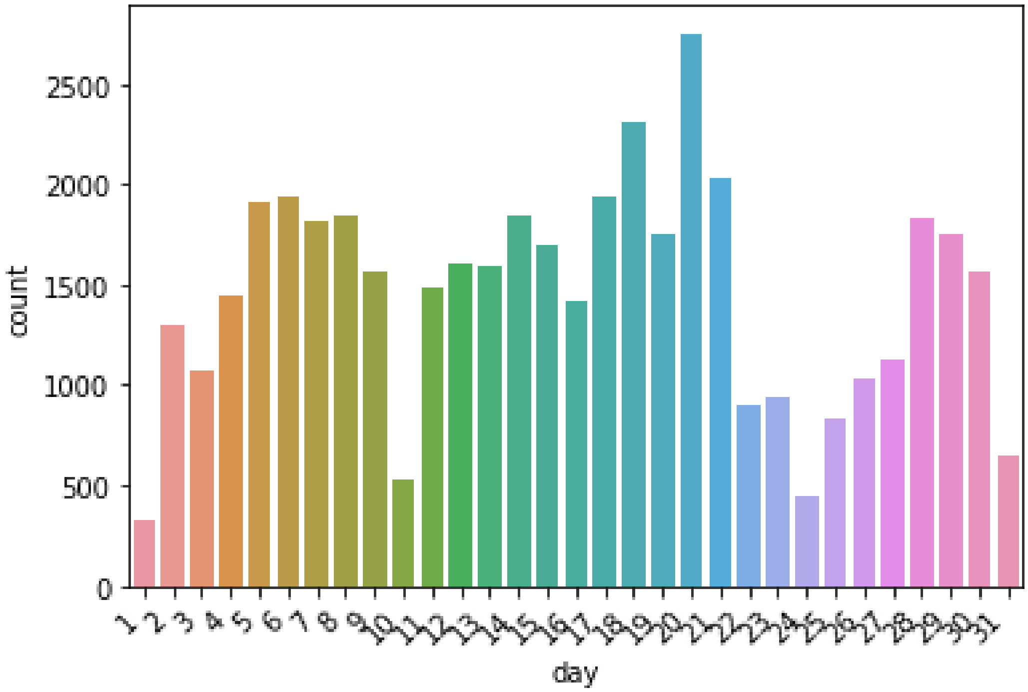
[273]:
```
sns.countplot(TDS.contact)
plt.xticks(rotation=45, horizontalalignment='right')

# Majority have cell phones
# Unknows will be flagged for later consideration
TDS.contact.value_counts()
```

[273]:
```
cellular     29285
unknown      13020
telephone     2906
Name: contact, dtype: int64
```



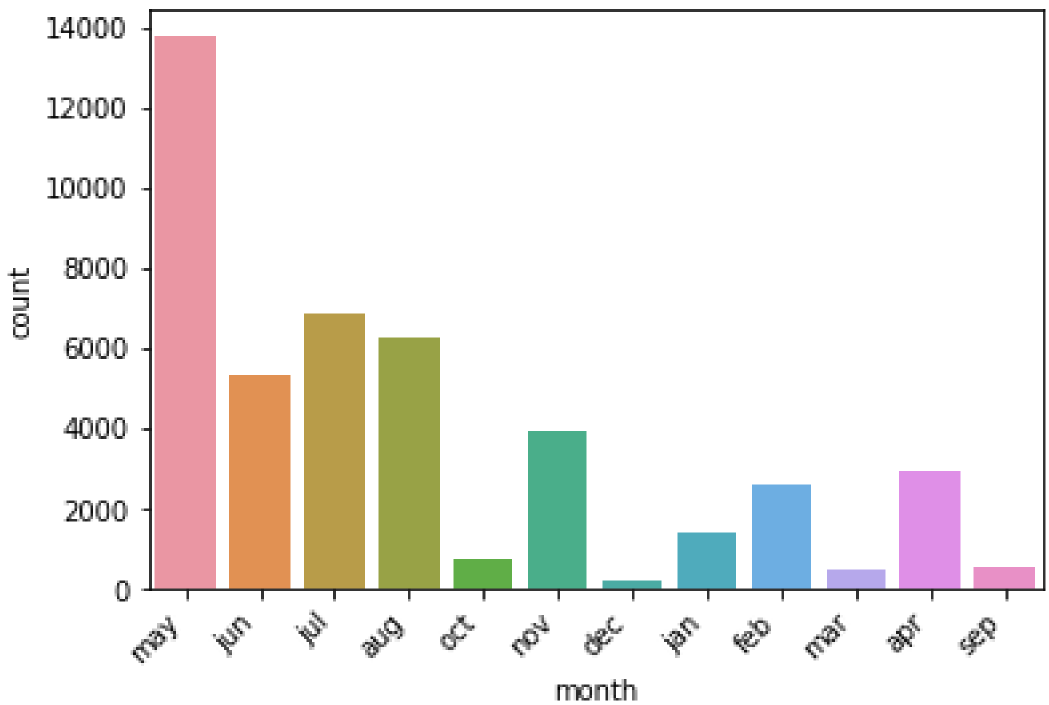
[274]:
```
sns.countplot(TDS.day)
plt.xticks(rotation=45, horizontalalignment='right')



# the day of the month is not equiprobable but spreadout. Pyschological factors␣
↪at play ?
# few days of the month seem to be lower than others:
'''
23      939
22      905
25      840
31      643
10      524
24      447
1       322
'''
```

[274]:
```
'\n23      939\n22      905\n25      840\n31      643\n10      524\n24      447\n1
322\n'
```



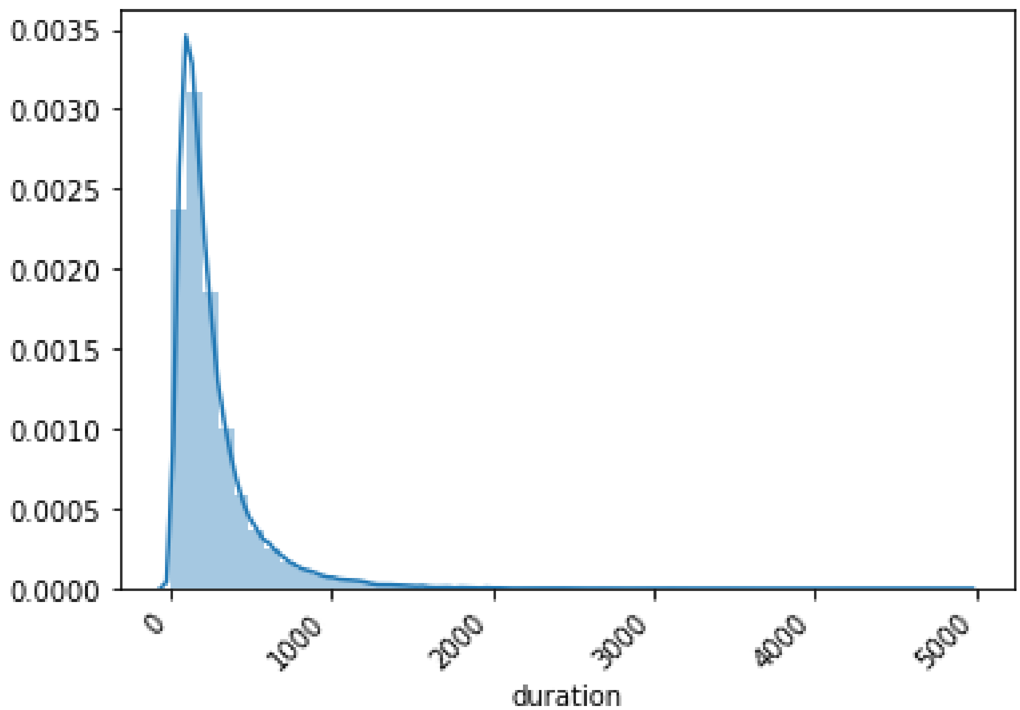
[275]:
```
sns.countplot(TDS.month)
plt.xticks(rotation=45, horizontalalignment='right')

# Obviously some months are more active than others for contacts with clients.
# Maybe it is a limited promotional timing that was mainly launched in May.
TDS.month.value_counts()
```

[275]:
```
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
```



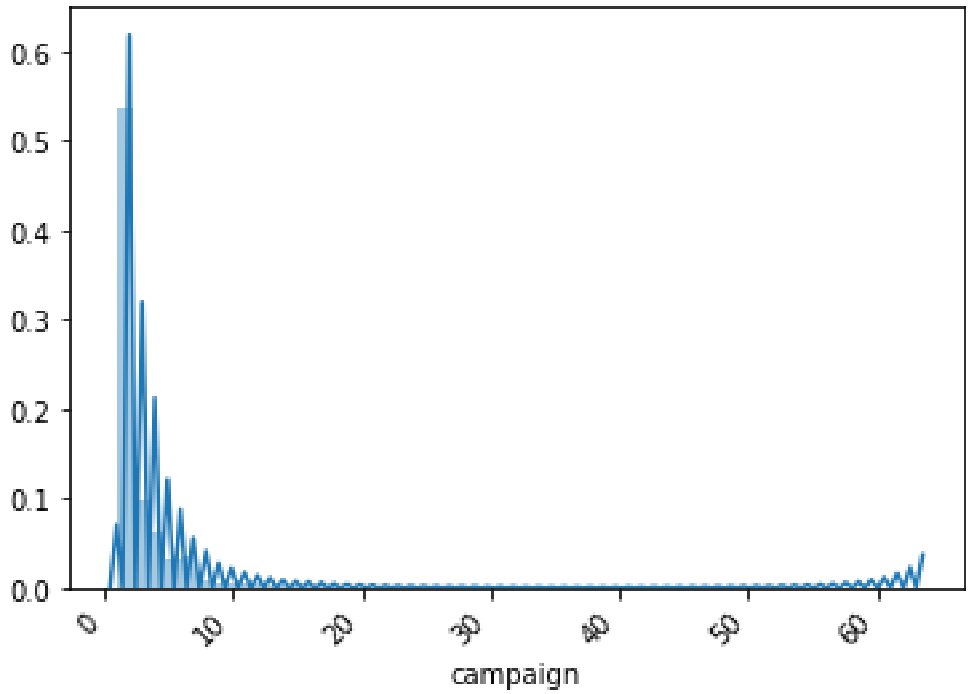
[276]:
```
sns.distplot(TDS.duration)
plt.xticks(rotation=45, horizontalalignment='right')

# A right skewed distrubution with many outliers, most calls are below 1000␣
↪seconds in length.
# but it was mentionned that it's preferable to drop it out of the model later␣
↪on.
# It could be that the longest calls resulted in positive outcomes for TDS so␣
↪we cannot make a cutoff .
```

[276]:
```
(array([-1000.,     0.,  1000.,  2000.,  3000.,  4000.,  5000.,  6000.]),
 <a list of 8 Text xticklabel objects>)
```



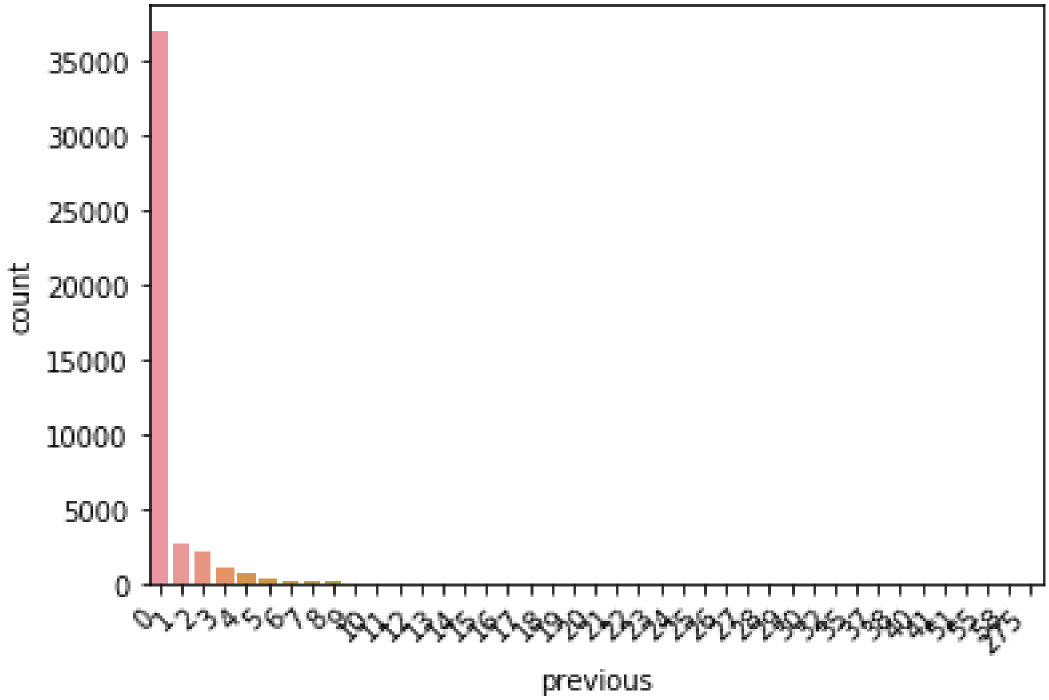
[277]:
```
sns.distplot(TDS.campaign)
plt.xticks(rotation=45, horizontalalignment='right')

# also 'campaign' very right skewed and could be correlated with 'duration'
```

[277]:
```
(array([-10.,   0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.]),
 <a list of 9 Text xticklabel objects>)
```



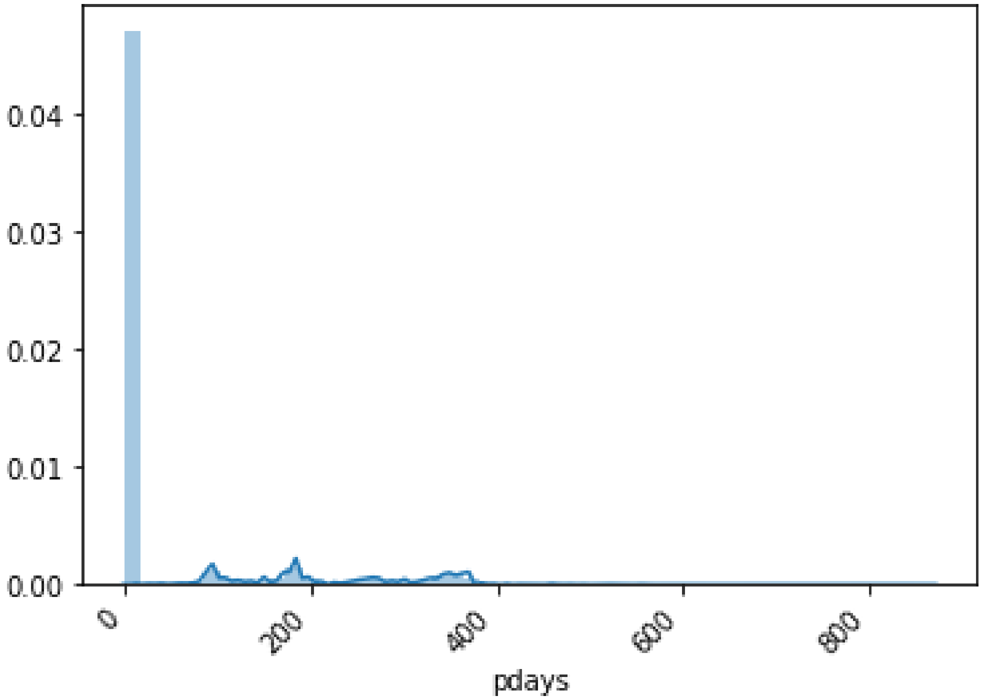
[278]:
```
sns.countplot(TDS.previous)
plt.xticks(rotation=45, horizontalalignment='right')

# also 'previous' campaign very right skewed and could be correlated with␣
↪'duration'
```

[278]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40]), <a list of 41 Text xticklabel objects>)
```



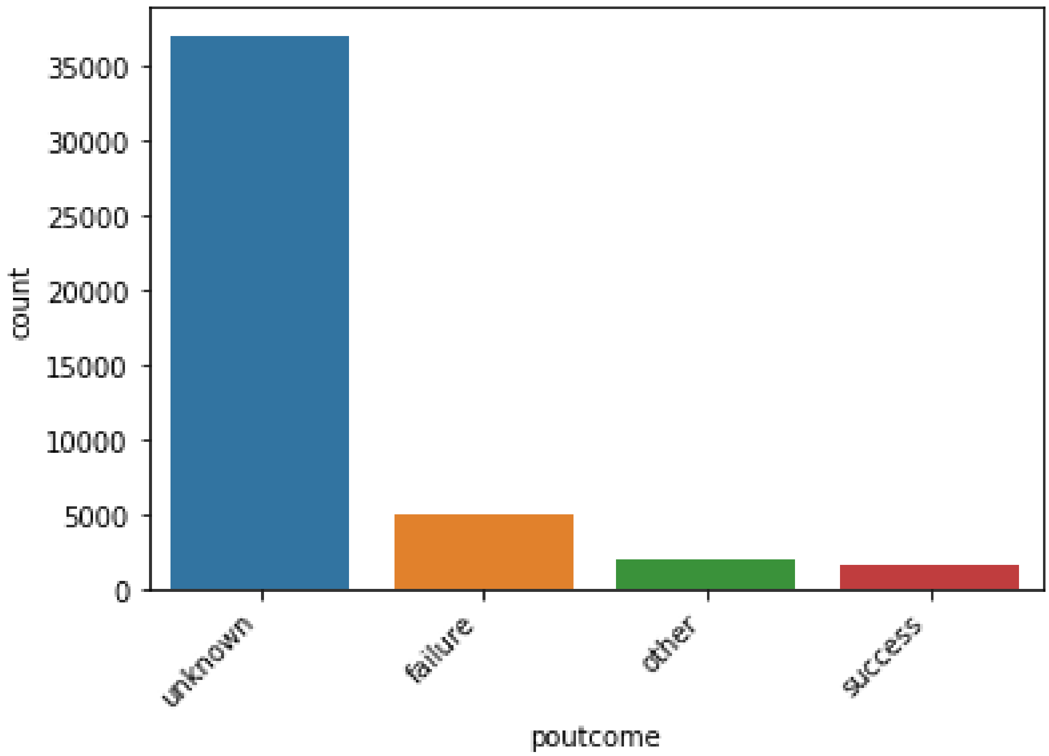

```
[279]: sns.distplot(TDS.pdays)
       plt.xticks(rotation=45, horizontalalignment='right')

       # '-1' is the majority who were not contacted
       TDS.pdays.value_counts()
```

```
[279]: -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
```



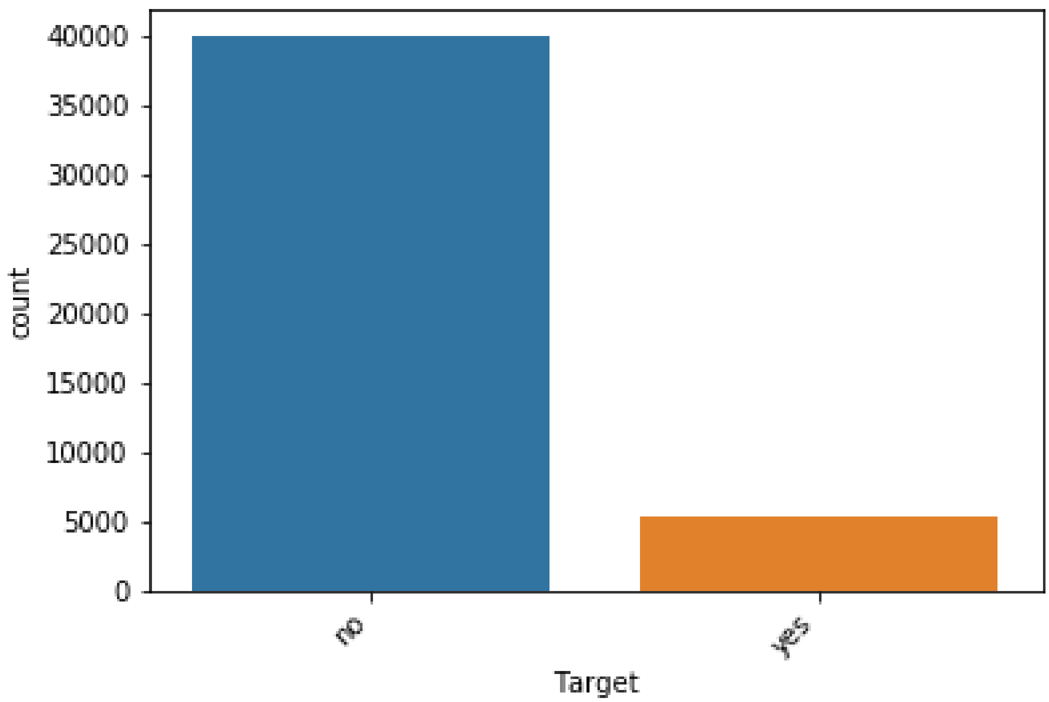
[280]:
```
sns.countplot(TDS.poutcome)
plt.xticks(rotation=45, horizontalalignment='right')

# 'unknown' is the majority who were not contacted in the previous campaign.␣
↪correltaed with the '-1' value above.
TDS.poutcome.value_counts()
```

[280]:
```
unknown    36959
failure     4901
other       1840
success     1511
Name: poutcome, dtype: int64
```



[281]:
```
sns.countplot(TDS.Target)
plt.xticks(rotation=45, horizontalalignment='right')

#  vast majority did not subscribe. Is it due to failure of being contact in a␣
 ↪previous campaign ?
TDS.Target.value_counts()
```

[281]:
```
no     39922
yes     5289
Name: Target, dtype: int64
```



2 2- Preparing Data for Analytics

Transforming attributes that are object or categorical and then proceed with joinplots to explore correlations

[282]:
```
TDS.dtypes
```

[282]:
```
age            int64
job           object
marital       object
education     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
```

```
Target        object
dtype: object
```

[283]:

```
# transforming object types columns into categorical

for column in TDS.columns:
    if TDS[column].dtype == 'object':
        TDS[column] = pd.Categorical(TDS[column])
```

[284]:

```
TDS.dtypes
# :-)
```

[284]:

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

[327]:

```
# now we have to use One-Hot encoding  for the columns: 'job' , 'marital',␣
 ↪'month'.
TDS_dummmies = pd.get_dummies(TDS, columns= ['job' , 'marital', 'month'])

TDS_dummies.head()
```

[327]:

```
   age  education default  balance housing loan  contact  day  duration  \
0   58   tertiary      no     2143     yes   no  unknown    5       261
1   44  secondary      no       29     yes   no  unknown    5       151
2   33  secondary      no        2     yes  yes  unknown    5        76
3   47    unknown      no     1506     yes   no  unknown    5        92
4   33    unknown      no        1      no   no  unknown    5       198

   campaign  …  month_dec  month_feb month_jan month_jul  month_jun  \
0         1  …          0          0         0         0          0
```

```
1          1  …          0          0          0          0          0
2          1  …          0          0          0          0          0
3          1  …          0          0          0          0          0
4          1  …          0          0          0          0          0

   month_mar  month_may  month_nov  month_oct  month_sep
0          0          1          0          0          0
1          0          1          0          0          0
2          0          1          0          0          0
3          0          1          0          0          0
4          0          1          0          0          0

[5 rows x 41 columns]
```

[348]:
```
TDS_dummies.Target.value_counts()
```

[348]:
```
no     39922
yes     5289
Name: Target, dtype: int64
```

[349]:
```
# Changing remaining categorical columns into ordinal scale & Creating new DF :␣
↪TDS_dummies_repl

replaceStruct = {
                "education": {'unknown': 0, 'primary': 1 ,'secondary': 2␣
↪,'tertiary':3},
                'default'  : {'yes': 0, 'no':1 },
                             # defaulting is not a good indicator hence 'yes'␣
↪--> 0
                'housing'  : {'no':1 , 'yes':0},
                'loan'     : {'no':1 , 'yes':0},
                'contact'  : {'unknown':0, 'telephone':1, 'cellular':2},
                'poutcome' : {'failure':-1,'unknown':0,'other':0, 'success':1},
                             # unknown and other considered same neutral level
                'Target'   : {'no':0 , 'yes':1},
                             # unknown and other considered same neutral level
                'pdays'    : {-1: 999}
                             #replacing -1 by 999 to show that client was never␣
↪contacted
                }
TDS_dummies_repl = TDS_dummies.replace(replaceStruct)

TDS_dummies_repl.head()

# All columns are numerical now :-) and hence correlations are possible!
```

[349]:
```
   age  education  default  balance  housing  loan  contact  day  duration  \
0   58          3        1     2143        0     1        0    5       261
1   44          2        1       29        0     1        0    5       151
2   33          2        1        2        0     0        0    5        76
3   47          0        1     1506        0     1        0    5        92
4   33          0        1        1        1     1        0    5       198

   campaign  …  month_dec  month_feb  month_jan  month_jul  month_jun  \
0         1  …          0          0          0          0          0
1         1  …          0          0          0          0          0
2         1  …          0          0          0          0          0
3         1  …          0          0          0          0          0
4         1  …          0          0          0          0          0

   month_mar  month_may  month_nov  month_oct  month_sep
0          0          1          0          0          0
1          0          1          0          0          0
2          0          1          0          0          0
3          0          1          0          0          0
4          0          1          0          0          0

[5 rows x 41 columns]
```

[331]:
```
TDS_dummies_repl.Target.value_counts()
```

[331]:
```
0    39922
1     5289
Name: Target, dtype: int64
```

[332]:
```
# SCALING numerical columns: age, balance, duration, campaign, pdays, previous

for col in TDS_dummies_repl.columns:

    if col   == 'age' :
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())
    elif col =='balance':
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())
    elif col =='duration':
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())
    elif col =='campaign':
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())
    elif col == 'pdays':
```

```
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())
    elif col =='previous':
        TDS_dummies_repl[col] = TDS_dummies_repl[col]/(TDS_dummies_repl[col].
 ↪max())

TDS_dummies_repl.head()
```

[332]:

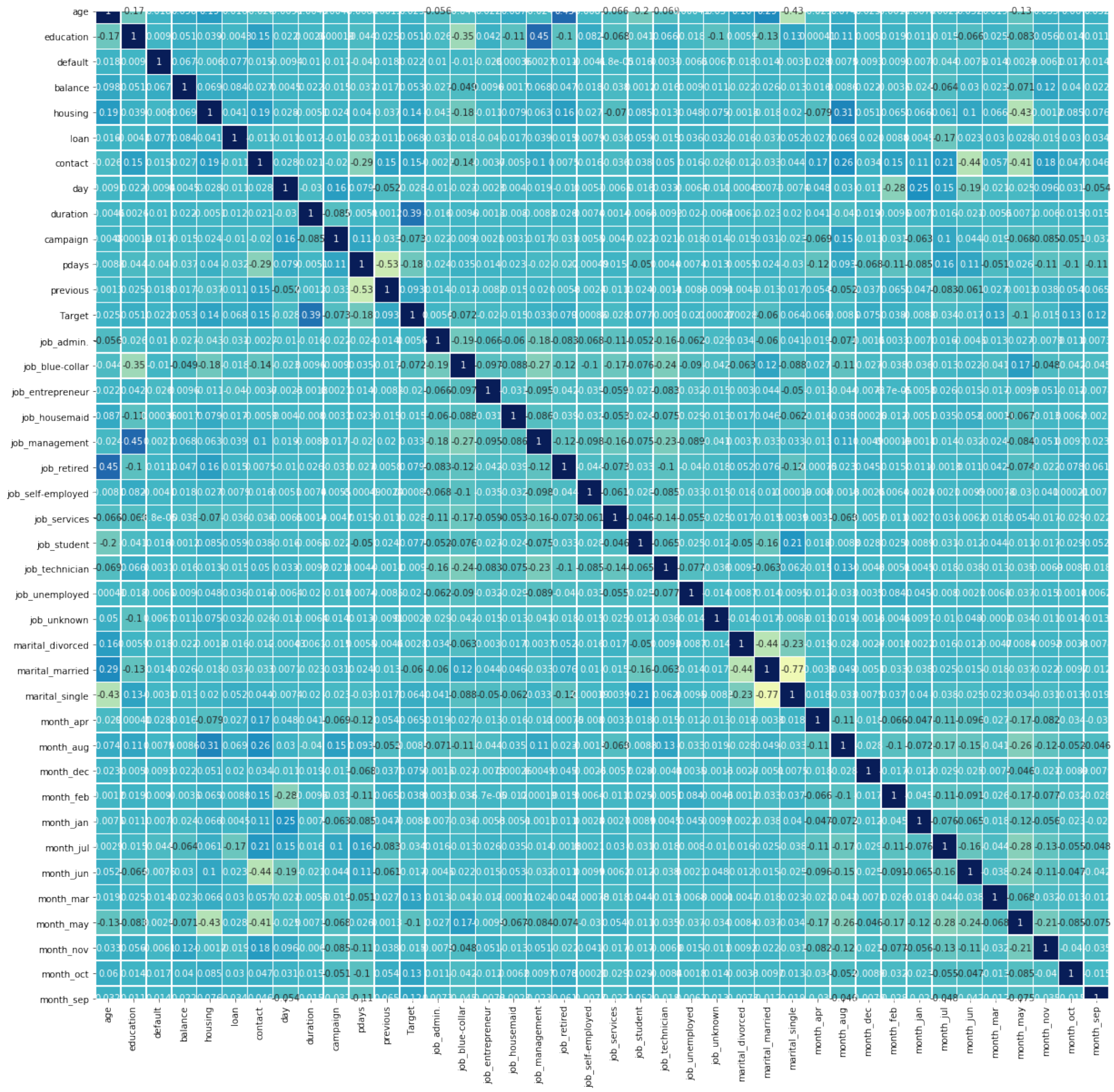
```
        age  education  default   balance  housing  loan  contact  day  \
0  0.610526          3        1  0.020984        0     1        0    5
1  0.463158          2        1  0.000284        0     1        0    5
2  0.347368          2        1  0.000020        0     0        0    5
3  0.494737          0        1  0.014746        0     1        0    5
4  0.347368          0        1  0.000010        1     1        0    5

   duration  campaign  …  month_dec  month_feb month_jan  month_jul  \
0  0.053070  0.015873  …          0          0         0          0
1  0.030704  0.015873  …          0          0         0          0
2  0.015453  0.015873  …          0          0         0          0
3  0.018707  0.015873  …          0          0         0          0
4  0.040260  0.015873  …          0          0         0          0

   month_jun  month_mar  month_may  month_nov  month_oct  month_sep
0          0          0          1          0          0          0
1          0          0          1          0          0          0
2          0          0          1          0          0          0
3          0          0          1          0          0          0
4          0          0          1          0          0          0

[5 rows x 41 columns]
```

[311]:

```
plt.figure(figsize=(20,20))

sns.heatmap( TDS_dummies_repl.corr(),
            annot=True,
            linewidths=.5,
            center=0,
            cbar=False,
            cmap="YlGnBu")

# NO Obvious Proxies with a correlation > 0.9 !
```

[311]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a4a133690>
```



[1]:
```
# NOTE : tried sns.pairplot( TDS_dummies_repl ) ... it was too computationally␣
↪heavy.
#couldn't get graphical resuts
```

3 3 and 4 - DT and Ensemble Models and comparison of performance

[368]:
```
# Importing the needed sklearn packages

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, recall_score,␣
↪precision_score, confusion_matrix
```

```python
from sklearn.tree     import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
```

[350]:
```python
TDS_dummies_repl.info()

# all columns are numerical types
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 41 columns):
age                  45211 non-null int64
education            45211 non-null int64
default              45211 non-null int64
balance              45211 non-null int64
housing              45211 non-null int64
loan                 45211 non-null int64
contact              45211 non-null int64
day                  45211 non-null int64
duration             45211 non-null int64
campaign             45211 non-null int64
pdays                45211 non-null int64
previous             45211 non-null int64
poutcome             45211 non-null int64
Target               45211 non-null int64
job_admin.           45211 non-null uint8
job_blue-collar      45211 non-null uint8
job_entrepreneur     45211 non-null uint8
job_housemaid        45211 non-null uint8
job_management       45211 non-null uint8
job_retired          45211 non-null uint8
job_self-employed    45211 non-null uint8
job_services         45211 non-null uint8
job_student          45211 non-null uint8
job_technician       45211 non-null uint8
job_unemployed       45211 non-null uint8
job_unknown          45211 non-null uint8
marital_divorced     45211 non-null uint8
marital_married      45211 non-null uint8
marital_single       45211 non-null uint8
month_apr            45211 non-null uint8
month_aug            45211 non-null uint8
month_dec            45211 non-null uint8
month_feb            45211 non-null uint8
month_jan            45211 non-null uint8
month_jul            45211 non-null uint8
```

```
month_jun             45211 non-null uint8
month_mar             45211 non-null uint8
month_may             45211 non-null uint8
month_nov             45211 non-null uint8
month_oct             45211 non-null uint8
month_sep             45211 non-null uint8
dtypes: int64(14), uint8(27)
memory usage: 6.0 MB
```

3.1 3.1 split data

[399]:
```
X = TDS_dummies_repl.drop( ["Target","duration"], axis=1)
y = TDS_dummies_repl.Target
```

[400]:
```
print(X.shape)
print(y.shape)
```

```
(45211, 39)
(45211,)
```

[441]:
```
(X_train, X_test, y_train, y_test) = train_test_split(X, y, test_size=.30,␣
↪random_state=1)

print(X_test.shape)
print(y_test.shape)
```

```
(13564, 39)
(13564,)
```

3.2 3.2 Decision Tree model using GINI criteria

[402]:
```
dTree_Gini= DecisionTreeClassifier(criterion = 'gini', random_state=1)

dTree_Gini.fit(X_train, y_train)

print(dTree_Gini.score(X_train, y_train))
print(dTree_Gini.score(X_test, y_test))

# The expected overfitting is there with the training Data
```

```
1.0
0.8352255971689767
```

[461]:
```
y_pred_G = dTree_Gini.predict(X_test)

# CONFUSION matrix
cm = metrics.confusion_matrix(y_test, y_pred_G, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
```

```
                                    columns = [i for i in ["No","Yes"]])

df_cm
```

[461]:

	No	Yes
No	10787	1226
Yes	1009	542

[462]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_G))
print(metrics.recall_score(y_test, y_pred_G))
print(metrics.precision_score(y_test, y_pred_G))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8352255971689767
0.34945196647324306
0.3065610859728507
```

[404]:
```
print (pd.DataFrame(dTree_Gini.feature_importances_, columns = ["Imp"], index =
 X_train.columns))

# 'balance', 'age, 'day'  seems to be the most important features
```

```
                          Imp
age                  0.143323
education            0.031835
default              0.002503
balance              0.204176
housing              0.024161
loan                 0.012849
contact              0.013699
day                  0.120806
campaign             0.054560
pdays                0.046922
previous             0.024002
poutcome             0.098443
job_admin.           0.010719
job_blue-collar      0.012416
job_entrepreneur     0.004377
job_housemaid        0.004178
job_management       0.013014
job_retired          0.005220
job_self-employed    0.006320
job_services         0.010259
job_student          0.005797
job_technician       0.017345
job_unemployed       0.006367
job_unknown          0.000862
```

```
marital_divorced   0.005912
marital_married    0.009750
marital_single     0.007906
month_apr          0.007355
month_aug          0.009540
month_dec          0.004198
month_feb          0.009696
month_jan          0.004449
month_jul          0.007358
month_jun          0.012728
month_mar          0.011076
month_may          0.007761
month_nov          0.006384
month_oct          0.011306
month_sep          0.010429
```

3.3 3.3 Decision Tree model using GINI criteria and depth = 4 (Pruning)

[463]:
```python
dTree_Gini_4= DecisionTreeClassifier(criterion = 'gini', max_depth=4␣
↪,random_state=1)

dTree_Gini_4.fit(X_train, y_train)

print(dTree_Gini_4.score(X_train, y_train))
print(dTree_Gini_4.score(X_test, y_test))

# Testing results are much better than without pruning
```

```
0.8942395803709672
0.8951636685343557
```

[464]:
```python
y_pred_G4 = dTree_Gini_4.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_G4, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                         columns = [i for i in ["No","Yes"]])

df_cm
```

[464]:

	No	Yes
No	11828	185
Yes	1237	314

[465]:
```python
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_G4))
```

```python
print(metrics.recall_score(y_test, y_pred_G4))
print(metrics.precision_score(y_test, y_pred_G4))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8951636685343557
0.2024500322372663
0.6292585170340681
```

[419]:
```python
print (pd.DataFrame(dTree_Gini_4.feature_importances_, columns = ["Imp"], index␣
↪= X_train.columns))

# 'poutcome' seems to be the most important feature by large!
```

```
                        Imp
age                0.110006
education          0.000000
default            0.000000
balance            0.000000
housing            0.016810
loan               0.000000
contact            0.000000
day                0.024734
campaign           0.002670
pdays              0.016754
previous           0.000000
poutcome           0.661688
job_admin.         0.000000
job_blue-collar    0.000000
job_entrepreneur   0.000000
job_housemaid      0.000000
job_management     0.000000
job_retired        0.000000
job_self-employed  0.000000
job_services       0.000000
job_student        0.000000
job_technician     0.002572
job_unemployed     0.000000
job_unknown        0.000000
marital_divorced   0.004168
marital_married    0.000000
marital_single     0.000000
month_apr          0.000000
month_aug          0.000000
month_dec          0.004339
month_feb          0.000000
month_jan          0.000000
month_jul          0.000000
month_jun          0.000000
```

```
month_mar          0.074116
month_may          0.007426
month_nov          0.000000
month_oct          0.074716
month_sep          0.000000
```

3.4 3.4 Decision Tree model using Entropy criteria

[475]:
```
dTree_Entropy= DecisionTreeClassifier(criterion = 'entropy' ,random_state=1)

dTree_Entropy.fit(X_train, y_train)

print(dTree_Entropy.score(X_train, y_train))
print(dTree_Entropy.score(X_test, y_test))

# Overfitting expected with training data
```

```
1.0
0.8347095252138013
```

[476]:
```
y_pred_E= dTree_Entropy.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_E, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                        columns = [i for i in ["No","Yes"]])

df_cm
```

[476]:

	No	Yes
No	10828	1185
Yes	1057	494

[477]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_E))
print(metrics.recall_score(y_test, y_pred_E))
print(metrics.precision_score(y_test, y_pred_E))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8347095252138013
0.3185041908446164
0.2942227516378797
```

[422]:
```
print (pd.DataFrame(dTree_Entropy.feature_importances_, columns = ["Imp"],␣
 ↪index = X_train.columns))
```

```
# 'balance', 'age' , 'day' seem to be the most important features
```

```
                       Imp
age                 0.144494
education           0.036393
default             0.002601
balance             0.219630
housing             0.016815
loan                0.013681
contact             0.030039
day                 0.112352
campaign            0.059784
pdays               0.046608
previous            0.019791
poutcome            0.081725
job_admin.          0.013046
job_blue-collar     0.015027
job_entrepreneur    0.004365
job_housemaid       0.002829
job_management      0.013128
job_retired         0.003448
job_self-employed   0.006259
job_services        0.010182
job_student         0.003707
job_technician      0.011517
job_unemployed      0.005701
job_unknown         0.002033
marital_divorced    0.007445
marital_married     0.009797
marital_single      0.008096
month_apr           0.012160
month_aug           0.007104
month_dec           0.003841
month_feb           0.008604
month_jan           0.004092
month_jul           0.006509
month_jun           0.011545
month_mar           0.009458
month_may           0.008560
month_nov           0.007789
month_oct           0.010675
month_sep           0.009170
```

3.5 3.5 Decision Tree model using Entropy criteria and depth = 4 (Pruning)

[423]:
```
dTree_Entropy_4= DecisionTreeClassifier(criterion = 'entropy', max_depth=4␣
↪,random_state=1)

dTree_Entropy_4.fit(X_train, y_train)

print(dTree_Entropy_4.score(X_train, y_train))
print(dTree_Entropy_4.score(X_test, y_test))

# Testing results are much better than without pruning
```

```
0.8927228489272285
0.8956797404895311
```

[478]:
```
y_pred_E4 = dTree_Entropy_4.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_E4, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                          columns = [i for i in ["No","Yes"]])

df_cm
```

[478]:

	No	Yes
No	11866	147
Yes	1268	283

[479]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_E4))
print(metrics.recall_score(y_test, y_pred_E4))
print(metrics.precision_score(y_test, y_pred_E4))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8956797404895311
0.1824629271437782
0.6581395348837209
```

[425]:
```
print (pd.DataFrame(dTree_Entropy_4.feature_importances_, columns = ["Imp"],␣
↪index = X_train.columns))

# 'poutcome' seems to be the most important feature by far
```

```
                    Imp
age            0.096045
education      0.000000
default        0.000000
```

```
balance            0.000000
housing            0.011200
loan               0.000000
contact            0.184645
day                0.014742
campaign           0.000000
pdays              0.009188
previous           0.000000
poutcome           0.584279
job_admin.         0.000000
job_blue-collar    0.000000
job_entrepreneur   0.000000
job_housemaid      0.000000
job_management     0.000000
job_retired        0.000000
job_self-employed  0.000000
job_services       0.000000
job_student        0.000000
job_technician     0.002000
job_unemployed     0.000000
job_unknown        0.000000
marital_divorced   0.000000
marital_married    0.008561
marital_single     0.000000
month_apr          0.000000
month_aug          0.000000
month_dec          0.000000
month_feb          0.000000
month_jan          0.000000
month_jul          0.000000
month_jun          0.074695
month_mar          0.000000
month_may          0.004646
month_nov          0.000000
month_oct          0.010000
month_sep          0.000000
```

4 Ensemble Methods

4.1 3.6 Random Forest model

[471]:
```
RFcl = RandomForestClassifier(n_estimators = 10, random_state=1,max_features=12)
RFcl = RFcl.fit(X_train, y_train)

print(RFcl.score(X_train, y_train))
print(RFcl.score(X_test, y_test))
```

```
0.9855594527127374
```

0.8913299911530522

[472]:
```
y_pred_RF = RFcl.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_RF, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                        columns = [i for i in ["No","Yes"]])

df_cm
```

[472]:

	No	Yes
No	11746	267
Yes	1207	344

[473]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_RF))
print(metrics.recall_score(y_test, y_pred_RF))
print(metrics.precision_score(y_test, y_pred_RF))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8913299911530522
0.22179239200515796
0.563011456628478
```

4.2 3.7 Adaboost Ensemble model

[468]:
```
ADcl = AdaBoostClassifier(n_estimators=10, random_state=1)

ADcl = ADcl.fit(X_train, y_train)

print(ADcl.score(X_train, y_train))
print(ADcl.score(X_test, y_test))
```

```
0.8912061174834898
0.8942789737540549
```

[469]:
```
y_pred_AD = ADcl.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_AD, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                        columns = [i for i in ["No","Yes"]])

df_cm
```

[469]:

	No	Yes
No	11809	204
Yes	1230	321

[470]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_AD))
print(metrics.recall_score(y_test, y_pred_AD))
print(metrics.precision_score(y_test, y_pred_AD))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8942789737540549
0.20696324951644102
0.6114285714285714
```

4.3 3.7 Bagging Ensemble model

[449]:
```
BGcl = BaggingClassifier(n_estimators=10,random_state=1)

BGcl = BGcl.fit(X_train, y_train)

print(BGcl.score(X_train, y_train))
print(BGcl.score(X_test, y_test))
```

```
0.9857174455714601
0.8900766735476261
```

[466]:
```
y_pred_BG = bgcl.predict(X_test)

# CONFUSION matrix

cm = metrics.confusion_matrix(y_test, y_pred_BG, labels=[0, 1])

df_cm = pd.DataFrame(cm, index = [i for i in ["No","Yes"]],
                     columns = [i for i in ["No","Yes"]])

df_cm
```

[466]:

	No	Yes
No	11696	317
Yes	1174	377

[467]:
```
print(' Accuracy - Recall - Precision scores respectively: ')
print(metrics.accuracy_score(y_test, y_pred_BG))
print(metrics.recall_score(y_test, y_pred_BG))
print(metrics.precision_score(y_test, y_pred_BG))
```

```
 Accuracy - Recall - Precision scores respectively:
0.8900766735476261
```

```
0.24306898774983882
0.5432276657060519
```

5 4-Conclusion :

5.0.1 Most models - whether a simple pruned DT or Ensemble methods - give similar performance on the Testing Data with Accuracy Scores approx = 90%.

5.0.2 However Precision and Recall scores are not so good for most models althought there are differences.

5.0.3 For the Ensemble methods , I did not provide a base model and used the default one , since even poor learners when agregated give good predictions. I kept the number of Trees to 10 for comaprison purposes and reduction of computationalal load as more did not provide significant imropvements in prediction capabilities .

Project 3 - Ensemble Techniques & Model Tuning

Thank you - Edouard Toutounji - 21 Feb 2020 .

[ ]:

```

```