Task-03 • Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository. • Sample Dateset :- https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

#Description

##Sources: • Created by: Paulo Cortez (Univ. Minho) and Sérgio Moro (ISCTE-IUL) @ 2012 • Dataset: The data related to the direct marketing campaigns conducted by a Portuguese banking institution.

##Problem Statement: • This is a binary classification problem. I built a decision tree classifier. The goal is to predict if the client contacted through the marketing campaign will subscribe to a term deposit. 0.1 Dataset Description: • The data is related with direct marketing campaigns of a Portuguese banking institution. • The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be (or not) subscribed. 0.2 Attribute information: • Number of Features : 45211 • Number of Attributes : 16 + output attribute. 0.3 Attributes Information: bank client data: * 1 - age:age of client(numeric) * 2 - job : type of job (categorical: “admin.”,“unknown”,“unemployed”,“management”,“housemaid”,“entrepreneur”,“student”,“bluecollar”,“self-employed”,“retired”,“technician”,“services”) * 3 - marital : marital status (categorical: “married”,“divorced”,“single”; note: “divorced” means divorced or widowed) * 4 - education (categorical: “unknown”,“secondary”,“primary”,“tertiary”) * 5 - default: has credit in default? (binary: “yes”,“no”) * 6 - balance: average yearly balance, in euros (numeric) * 7 - housing: has housing loan? (binary: “yes”,“no”) * 8 - loan: has personal loan? (binary: “yes”,“no”) related with the last contact of the current campaign: * 9 - contact: contact communication type 1 (categorical: “unknown”,“telephone”,“cellular”) * 10 - day: last contact day of the month (numeric) * 11 - month: last contact month of year (categorical: “jan”, “feb”, “mar”, …, “nov”, “dec”)

- 12 - duration: last contact duration, in seconds (numeric) other attributes: * 13 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact) * 14 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric, -1 means client was not previously contacted) * 15 - previous: number of contacts performed before this campaign and for this client (numeric) * 16 - poutcome: outcome of the previous marketing campaign (categorical: “unknown”,“other”,“failure”,“success”) Output variable (desired target): 17 - y - has the client subscribed a term deposit? (binary: “yes”,“no”)

1 Import necessary libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.metrics import
confusion_matrix,classification_report,accuracy_score
from mlxtend.plotting import plot_confusion_matrix
from sklearn import tree

from google.colab import files
raw = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving bank_data_set.csv to bank_data_set.csv
```

```
# Load the dataset
df=pd.read_csv('bank_data_set.csv')

df
```

```
       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
...    ...           ...       ...        ...     ...      ...     ...
...
45206   51    technician   married   tertiary      no      825      no
no
45207   71       retired  divorced    primary      no     1729      no
no
45208   72       retired   married  secondary      no     5715      no
no
45209   57   blue-collar   married  secondary      no      668      no
no
45210   37  entrepreneur   married  secondary      no     2971      no
no

         contact  day month  duration  campaign  pdays  previous
poutcome    y
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
...           ...  ...   ...        ...        ...    ...        ...
...  ...
45206   cellular   17   nov        977          3     -1          0
unknown  yes
45207   cellular   17   nov        456          2     -1          0
unknown  yes
45208   cellular   17   nov       1127          5    184          3
success  yes
45209  telephone   17   nov        508          4     -1          0
unknown   no
45210   cellular   17   nov        361          2    188         11
other   no

[45211 rows x 17 columns]
```

#Exploratory data analysis(EDA)

```
 # shallow copy
df2=df.copy()

#shape of a DataFrame.
df.shape

(45211, 17)

# Display all columns
df.columns

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

# displays the top rows of a DataFrame
df.head()

   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

   contact  day month  duration  campaign  pdays  previous poutcome
y
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
```

```
#shows the bottom rows
df.tail()
```

```
       age           job   marital  education default  balance housing
loan  \
45206   51    technician   married   tertiary      no      825      no
no
45207   71       retired  divorced    primary      no     1729      no
no
45208   72       retired   married  secondary      no     5715      no
no
45209   57   blue-collar   married  secondary      no      668      no
no
45210   37  entrepreneur   married  secondary      no     2971      no
no

         contact  day month  duration  campaign  pdays  previous
poutcome    y
45206   cellular   17   nov       977         3     -1         0
unknown  yes
45207   cellular   17   nov       456         2     -1         0
unknown  yes
45208   cellular   17   nov      1127         5    184         3
success  yes
45209  telephone   17   nov       508         4     -1         0
unknown   no
45210   cellular   17   nov       361         2    188        11
other   no
```

```
 # specific rows of a DataFrame ( "integer location" Method)
df.iloc[100:200]
```

```
     age          job   marital  education default  balance housing
loan  \
```

```
100   44  blue-collar   married  secondary      no     -674     yes
no
101   53  blue-collar   married    primary      no       90      no
no
102   52  blue-collar   married    primary      no      128     yes
no
103   59  blue-collar   married    primary      no      179     yes
no
104   27   technician    single   tertiary      no        0     yes
no
..   ...          ...       ...        ...     ...      ...     ...  .
..
195   33  blue-collar    single  secondary      no      307     yes
no
196   38     services   married  secondary      no      155     yes
no
197   50   technician  divorced   tertiary      no      173      no
yes
198   43   management   married   tertiary      no      400     yes
no
199   61  blue-collar  divorced    primary      no     1428     yes
no

     contact  day month  duration  campaign  pdays  previous poutcome
y
100  unknown    5   may       257         1     -1         0  unknown
no
101  unknown    5   may       124         1     -1         0  unknown
no
102  unknown    5   may       229         1     -1         0  unknown
no
103  unknown    5   may        55         3     -1         0  unknown
no
104  unknown    5   may       400         1     -1         0  unknown
no
..       ...  ...   ...       ...       ...    ...       ...      ...
..
195  unknown    5   may       309         2     -1         0  unknown
no
196  unknown    5   may       248         1     -1         0  unknown
no
197  unknown    5   may        98         1     -1         0  unknown
no
198  unknown    5   may       256         1     -1         0  unknown
no
199  unknown    5   may        82         2     -1         0  unknown
no

[100 rows x 17 columns]
```

```python
# prints information about the DataFrame.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

```python
# Display summary statistics for numerical columns in DataFrame.
df.describe().T
```

```
            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
```

```
# Dispaly (string) columns in the summary statistics.
df.describe(include=object)
```

```
                job  marital  education default housing   loan
contact  \
count         45211    45211      45211   45211   45211  45211
45211
unique           12        3          4       2       2      2
3
top     blue-collar  married  secondary      no     yes     no
cellular
freq           9732    27214      23202   44396   25130  37967
29285

        month poutcome      y
count   45211    45211  45211
unique     12        4      2
top       may  unknown     no
freq    13766    36959  39922
```

```
# numerical columns list
numerical_data=df.select_dtypes(include=['int64','float64']).columns.t
o_list()
numerical_data
```

```
['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous']
```

```
# object columns list
object_data=df.select_dtypes(include=['object']).columns.tolist()
print(object_data)
```

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

2 Data cleaning

```
# To check for duplicate values in a DataFrame
df.duplicated().sum()
```

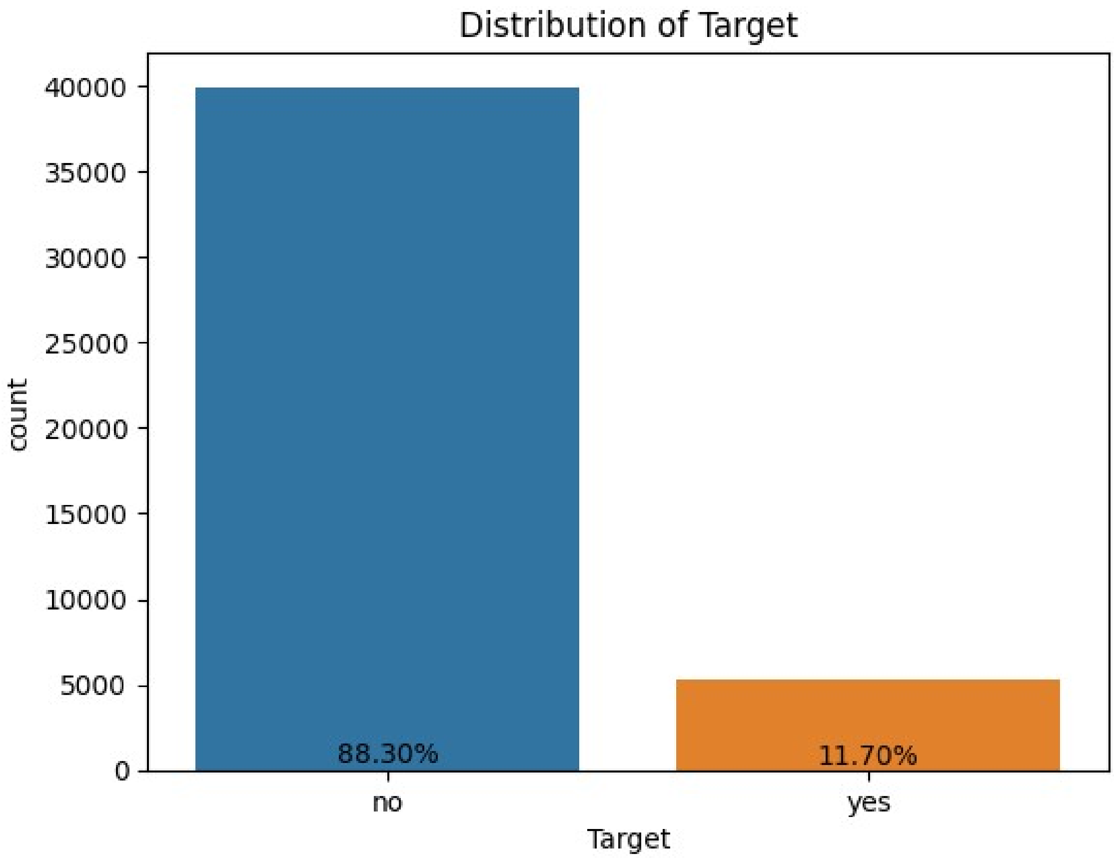
```
0
```

```
 # The number of missing values in the dataset.
df.isnull().sum()
```

```
age          0
job          0
marital      0
education    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
y            0
dtype: int64

#Observation: Our dataset do not have any null/nan/missing values.
```

3 visualization

```
sns.countplot(x=df['y'])
plt.title('Distribution of Target')
plt.xlabel('Target')
value_counts = df['y'].value_counts()/df.shape[0]*100
for i, count in enumerate(value_counts):
   plt.text(i, count, f'{count:.2f}%', ha='center', va='bottom') # i
for index # count for values # print the count which formatting
```




```
# Observation: dataset is highly imbalanced.
```

4 Outliers

```
# Calculate the IQR (Interquartile Range)
Q1 = df[numerical_data].quantile(0.25)
Q3 = df[numerical_data].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_outliers_removed = df[(df[numerical_data] >= lower_bound) &
(df[numerical_data] <= upper_bound)]
df_outliers_removed.describe()
```

```
                age        balance            day       duration
campaign  \
count  44724.000000   40482.000000   45211.000000   41976.000000
42147.000000
mean      40.545524     640.636233      15.806419     203.490947
2.129950
std        9.978232     844.435442       8.322476     140.805074
1.315842
min       18.000000   -1944.000000       1.000000       0.000000
```

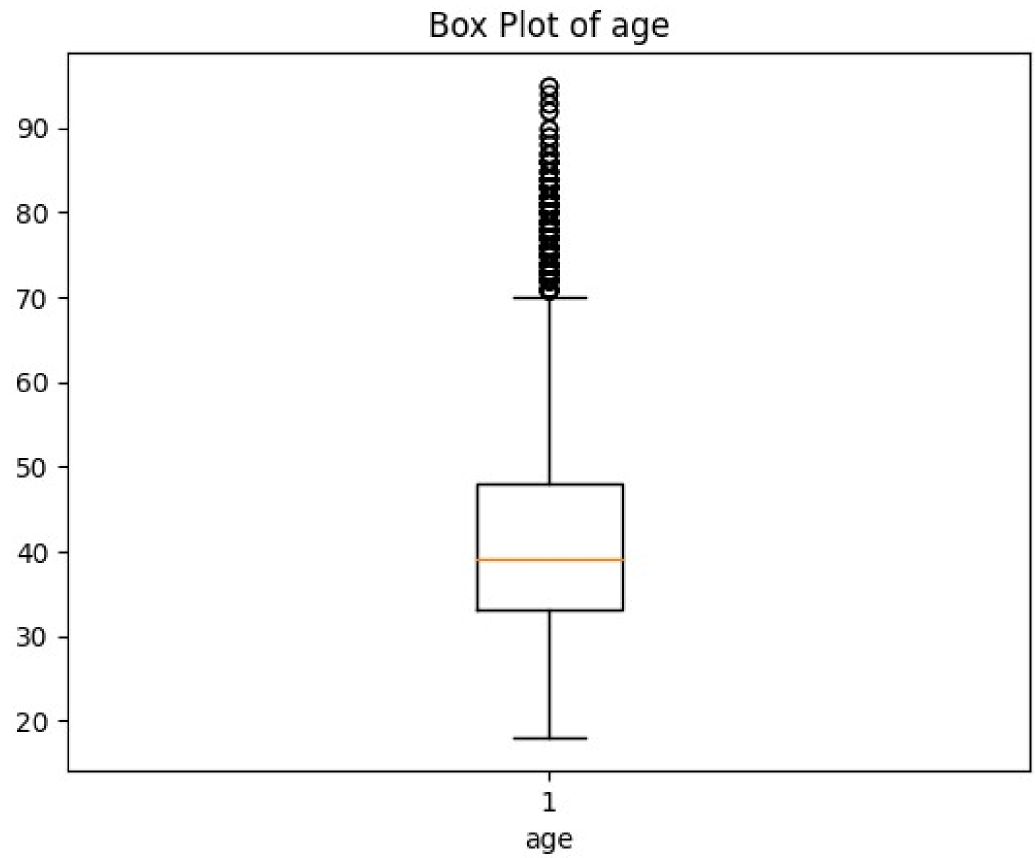
```
1.000000
25%        33.000000     46.000000      8.000000     98.000000
1.000000
50%        39.000000    349.000000     16.000000    167.000000
2.000000
75%        48.000000    980.750000     21.000000    277.000000
3.000000
max        70.000000   3462.000000     31.000000    643.000000
6.000000
```

```
         pdays  previous
count  36954.0   36954.0
mean      -1.0       0.0
std        0.0       0.0
min       -1.0       0.0
25%       -1.0       0.0
50%       -1.0       0.0
75%       -1.0       0.0
max       -1.0       0.0
```

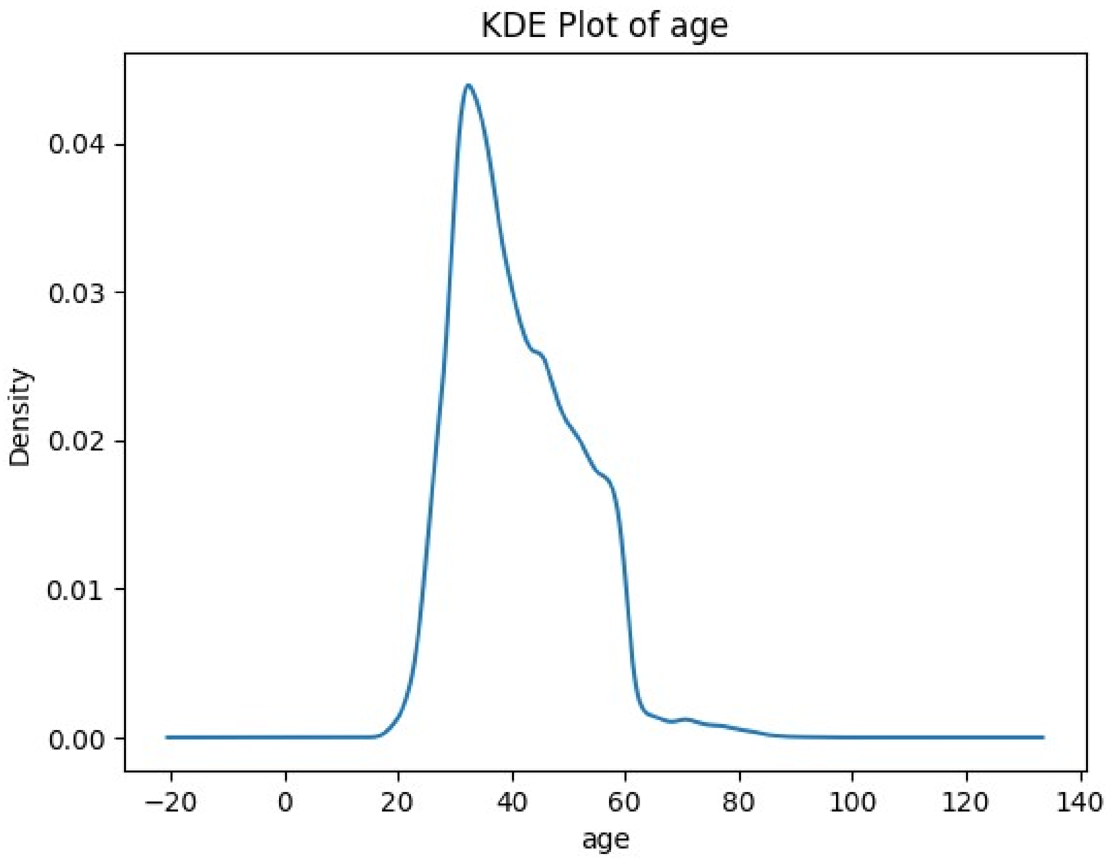
```
def remove_outliers(df, column):
# Calculate the IQR (Interquartile Range)
   Q1 = df[column].quantile(0.25)
   Q3 = df[column].quantile(0.75)
   IQR = Q3 - Q1
   lower_bound = Q1 - 1.5 * IQR
   upper_bound = Q3 + 1.5 * IQR
   df_outliers_removed = df[(df[column] >= lower_bound) & (df[column]
<= upper_bound)]
   return df_outliers_removed
```

```
plt.boxplot(x=df['age'])
plt.xlabel('age')
plt.title('Box Plot of age')
```

```
Text(0.5, 1.0, 'Box Plot of age')
```




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

count    45211.000000
mean        40.936210
std         10.618762
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64

df['age'].plot.kde()
plt.xlabel('age')
plt.title('KDE Plot of age')

Text(0.5, 1.0, 'KDE Plot of age')
```




```
df.shape
```

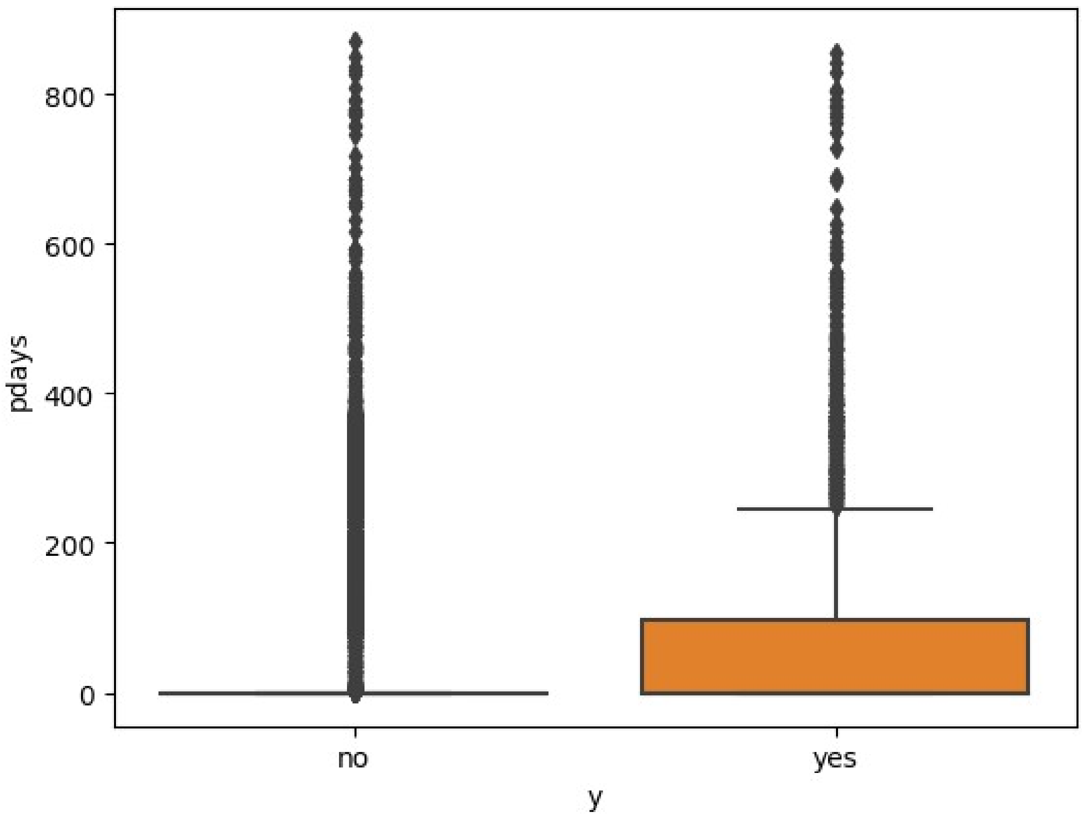
```
(45211, 17)
```

```
# Remove outliers
df=remove_outliers(df,'age')
df['age'].describe()
```

```
count    44724.000000
mean        40.545524
std          9.978232
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         70.000000
Name: age, dtype: float64
```

```
sns.boxplot(y=df['pdays'],x=df['y'])
```

```
<Axes: xlabel='y', ylabel='pdays'>
```




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

```
count    44724.000000
mean        40.000000
std        100.193608
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

```
# Remove outliers
df=remove_outliers(df,'pdays')
```

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

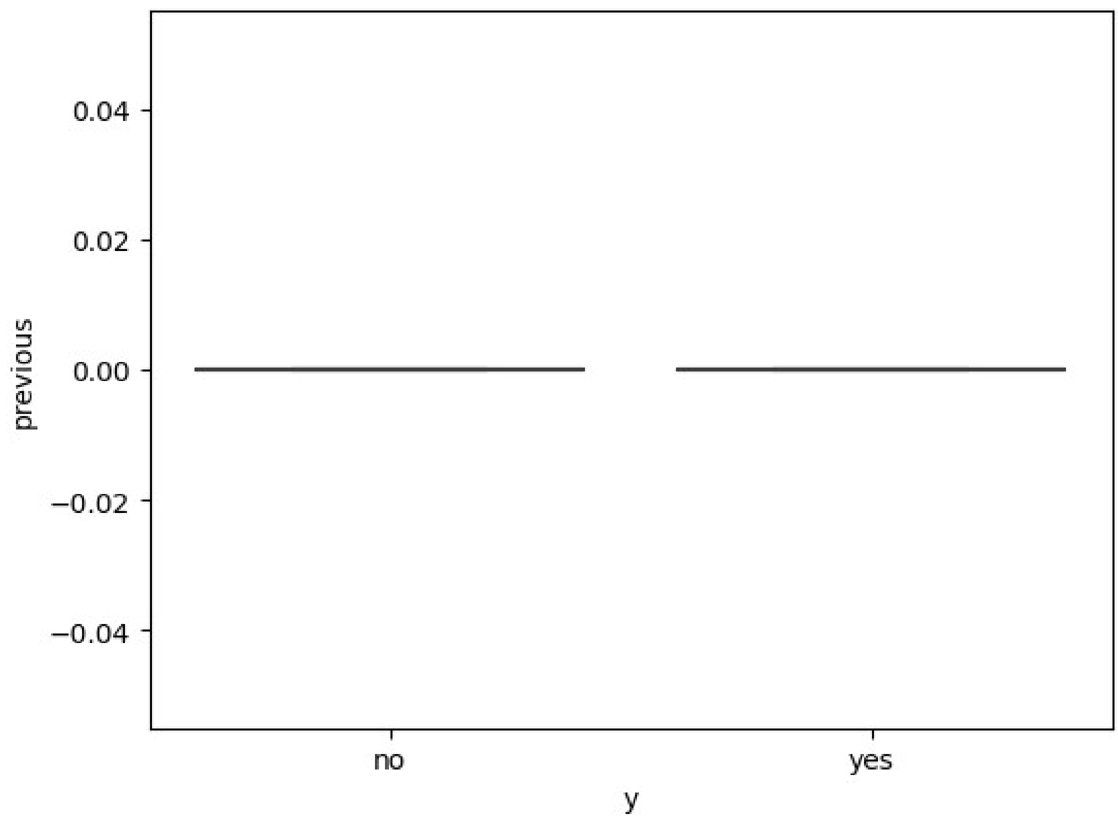
```
count    36648.0
mean        -1.0
std          0.0
min         -1.0
25%         -1.0
50%         -1.0
75%         -1.0
```

```
max          -1.0
Name: pdays, dtype: float64
```

Observation: * There are outliers ('pdays) as we can see from boxplot. * after outlier mean of Mean of pdays is -1

```
sns.boxplot(y=df['previous'],x=df['y'])
```

```
<Axes: xlabel='y', ylabel='previous'>
```




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

```
count    36648.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          0.0
Name: previous, dtype: float64
```

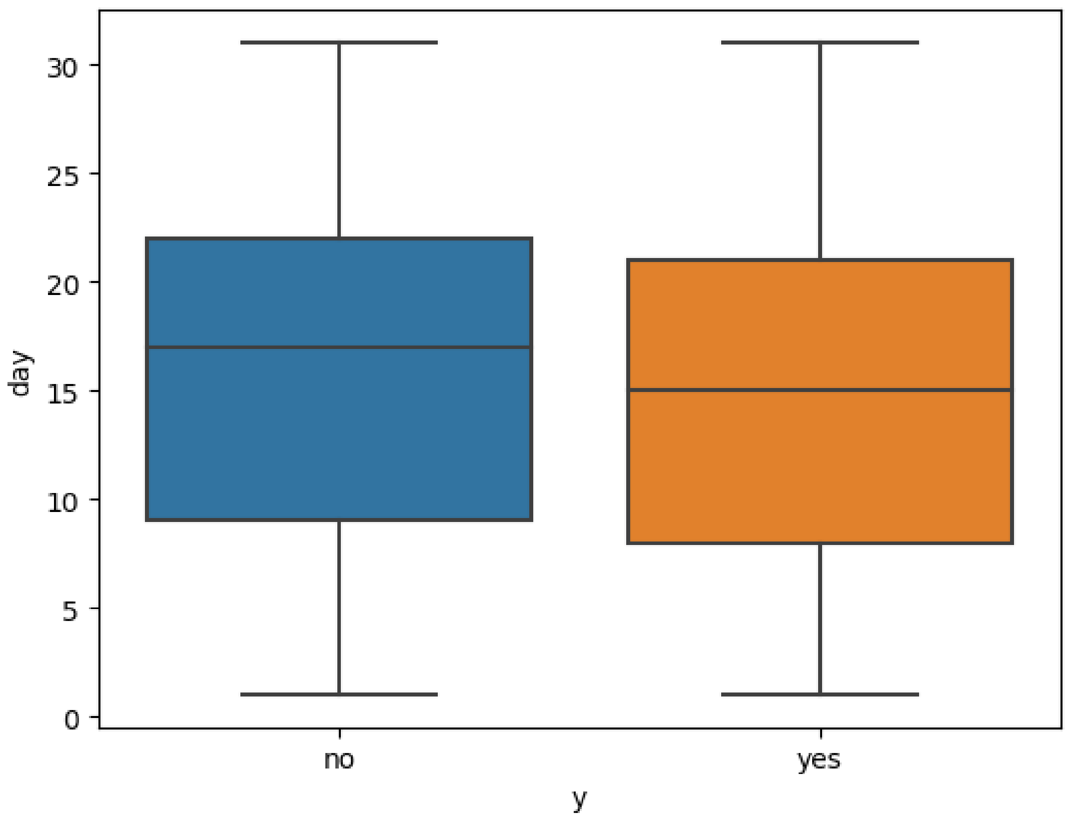
```
# Remove outliers
df=remove_outliers(df,'previous')
df['previous'].describe()
```

```
count    36648.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          0.0
Name: previous, dtype: float64
```

Observation: * There are outliers (previous) already remove ('Pday') columns * after outliers all describe function maximum 0

```
sns.boxplot(y=df['day'],x=df['y'])
```

```
<Axes: xlabel='y', ylabel='day'>
```



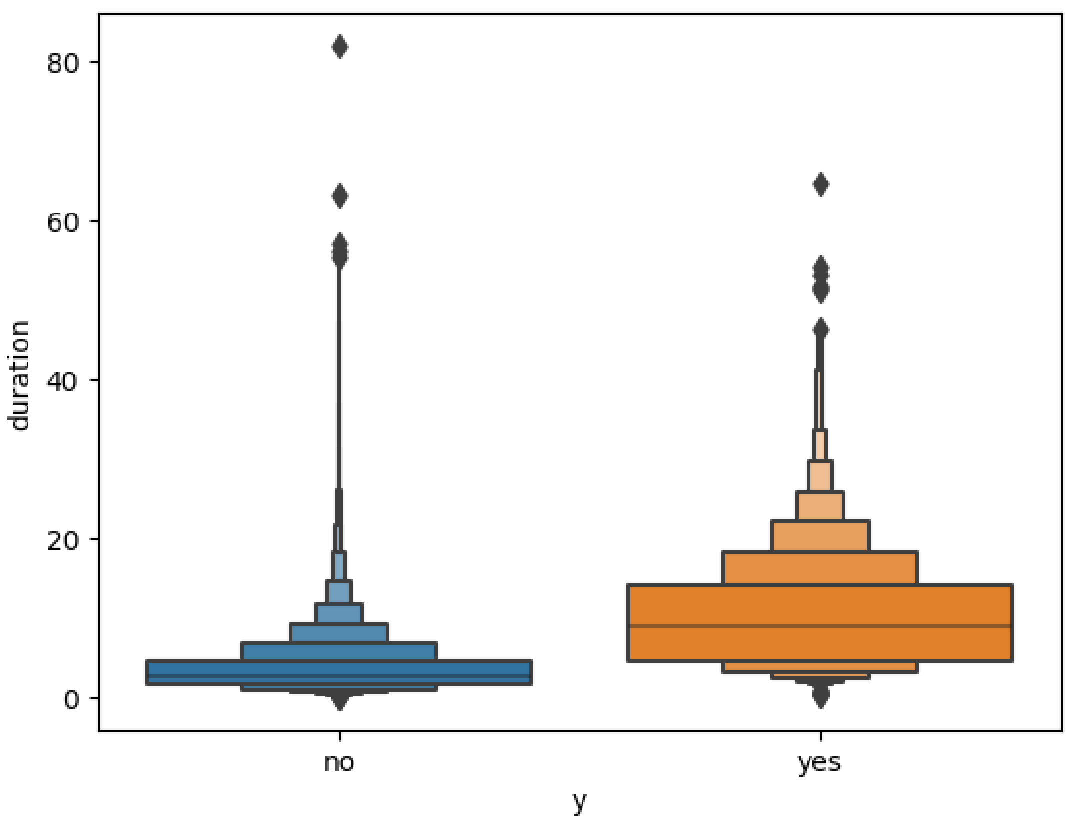
Observation: * There are no outliers (days) as we can see from boxplot.

```
# converting call duration from seconds to minute
df['duration'] = df['duration']/60

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

```
count    36648.000000
mean         4.288495
std          4.372761
min          0.000000
25%          1.683333
50%          2.950000
75%          5.283333
max         81.966667
Name: duration, dtype: float64
```

```
sns.boxenplot(y=df['duration'],x=df['y'])
```

```
<Axes: xlabel='y', ylabel='duration'>
```




```
# Remove outliers
df=remove_outliers(df,'duration')
df['duration'].describe()
```

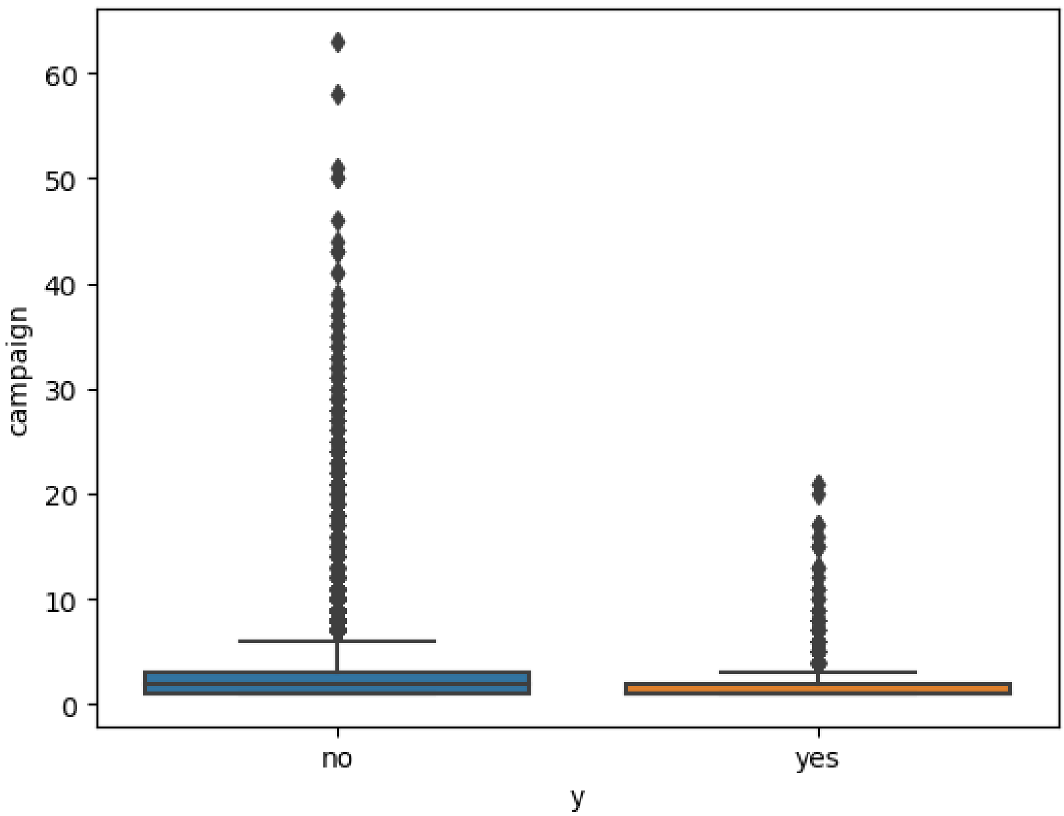
```
count    33949.000000
mean         3.342183
```

```
std           2.338945
min           0.000000
25%           1.600000
50%           2.733333
75%           4.533333
max          10.683333
Name: duration, dtype: float64
```

Observation: * There are outliers ('duration') as we can see from boxplot. * after outliers maximum of duration 10

```
sns.boxplot(y=df['campaign'],x=df['y'])
```

```
<Axes: xlabel='y', ylabel='campaign'>
```




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

```
count    33949.000000
mean         2.943828
std          3.376793
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
```

```
max           63.000000
Name: campaign, dtype: float64
```

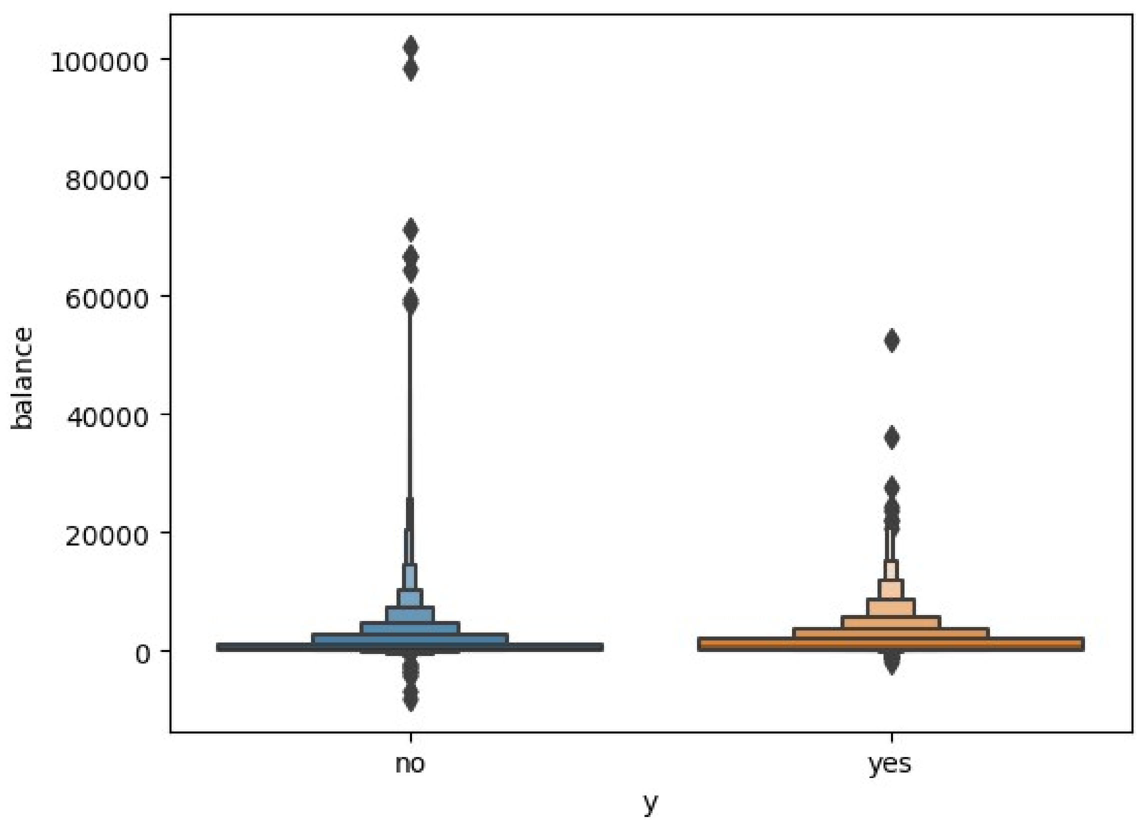
```
# Remove outliers
df=remove_outliers(df,'campaign')
df['campaign'].describe()
```

```
count    31275.000000
mean         2.185995
std          1.341735
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
max          6.000000
Name: campaign, dtype: float64
```

Observation: * There are outliers (campaign) as we can see from boxplot. * after outliers maximum of campaign 6.0

```
sns.boxenplot(x=df['y'],y=df['balance'])
```

```
<Axes: xlabel='y', ylabel='balance'>
```



```python
df['balance'].describe()
```

```
count     31275.000000
mean       1299.529816
std        3045.431847
min       -8019.000000
25%          53.000000
50%         406.000000
75%        1334.500000
max      102127.000000
Name: balance, dtype: float64
```

```python
# Remove outliers
df=remove_outliers(df,'balance')
df['balance'].describe()
```

```
count    27930.000000
mean       583.151916
std        794.690176
min      -1854.000000
25%         30.000000
50%        311.000000
75%        892.750000
max       3255.000000
Name: balance, dtype: float64
```

Observation: * There are outliers ('balance') as we can see from boxplot. * after outlier mean of 583

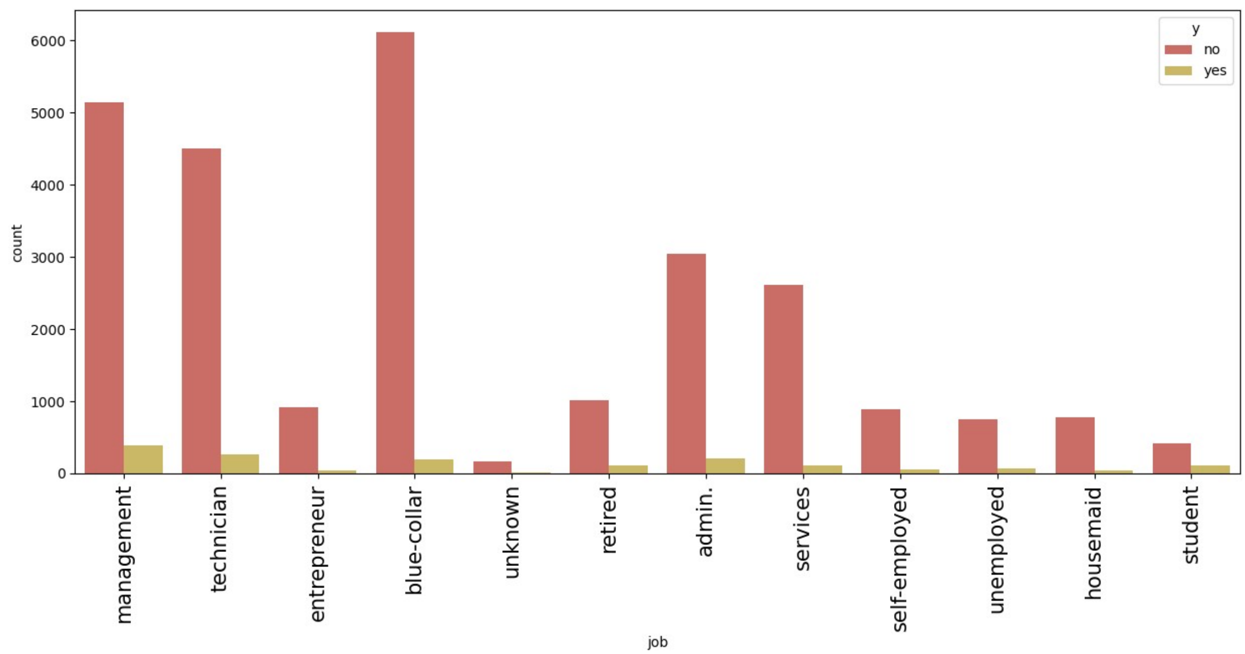
```python
df.isnull().sum()
```

```
age          0
job          0
marital      0
education    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
y            0
dtype: int64
```

```
object_data
```

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

```
plt.figure(figsize=(15, 6))
jobs=df['job'].value_counts().sort_values(ascending=False)
sns.countplot(x=df['job'],
hue=df['y'],palette=sns.color_palette("hls", 8))
plt.xticks(rotation=90,fontsize=15)
plt.show()
```




```
jobs
```

```
blue-collar      6308
management       5531
technician       4764
admin.           3245
services         2724
retired          1128
entrepreneur      958
```

```
self-employed      945
housemaid          813
unemployed         812
student            528
unknown            174
Name: job, dtype: int64
```

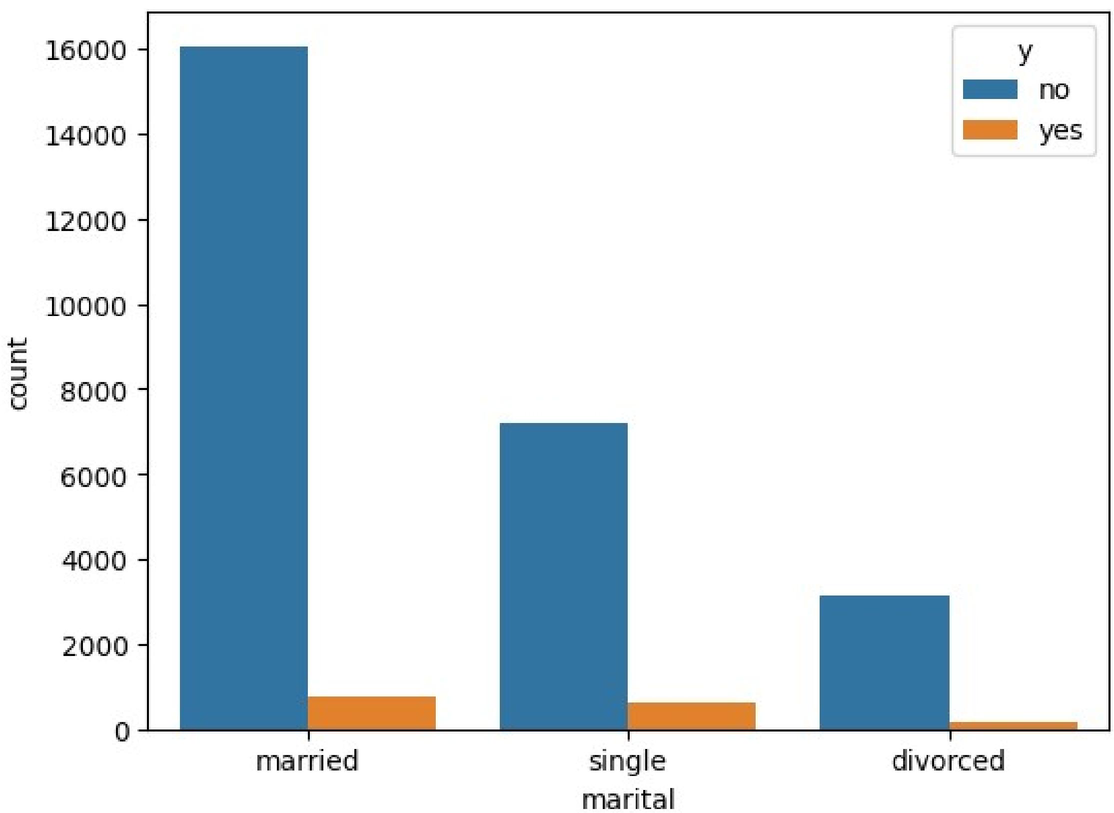
Observation: * Top contacted clients are from job type: ‘blue-collar’, ‘management’ & ‘technician’

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

```
married     16807
single       7822
divorced     3301
Name: marital, dtype: int64
```

```
sns.countplot(x=df['marital'],hue=df['y'])
```

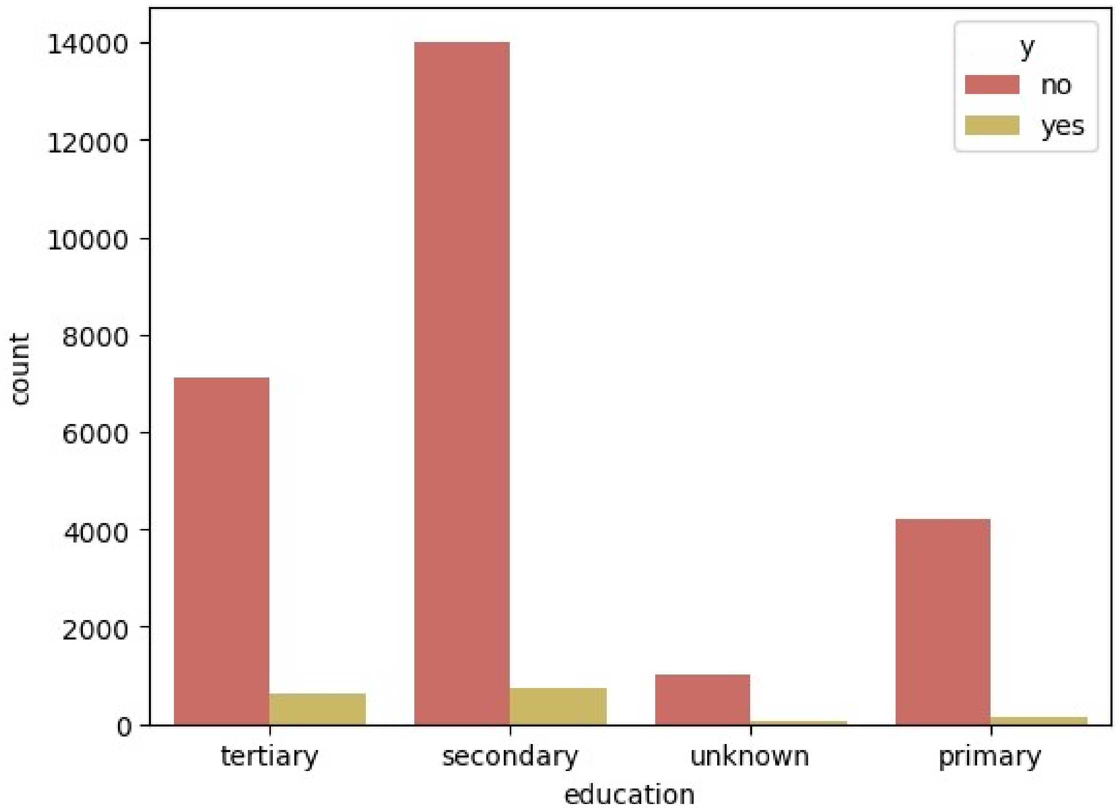
```
<Axes: xlabel='marital', ylabel='count'>
```



Observation: * Top client married

```
sns.countplot(x=df['education'],hue=df['y'],palette=sns.color_palette(
"hls", 8))
```

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



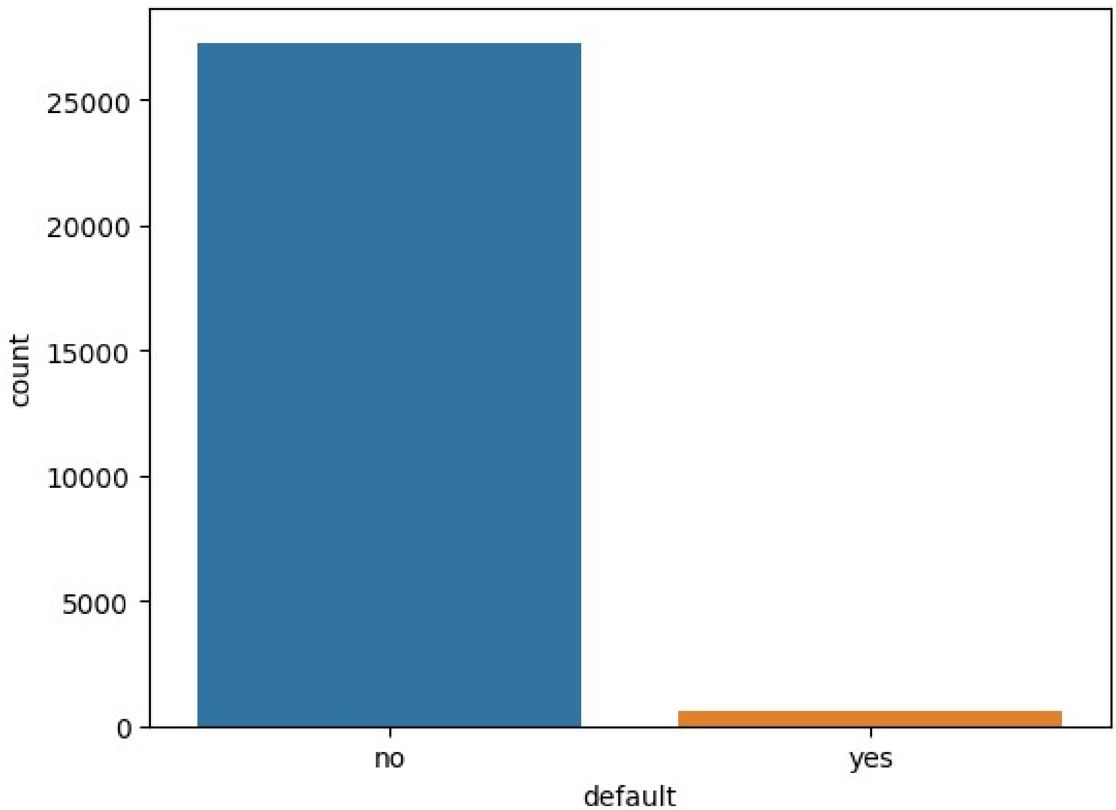
Observation • Most of the people who are contacted have secondary or tertiray education.

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

```
no     27304
yes      626
Name: default, dtype: int64
```

```
sns.countplot(x=df['default'])
```

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




```
df[df['default'] == 'yes'].y.count()
```

```
626
```

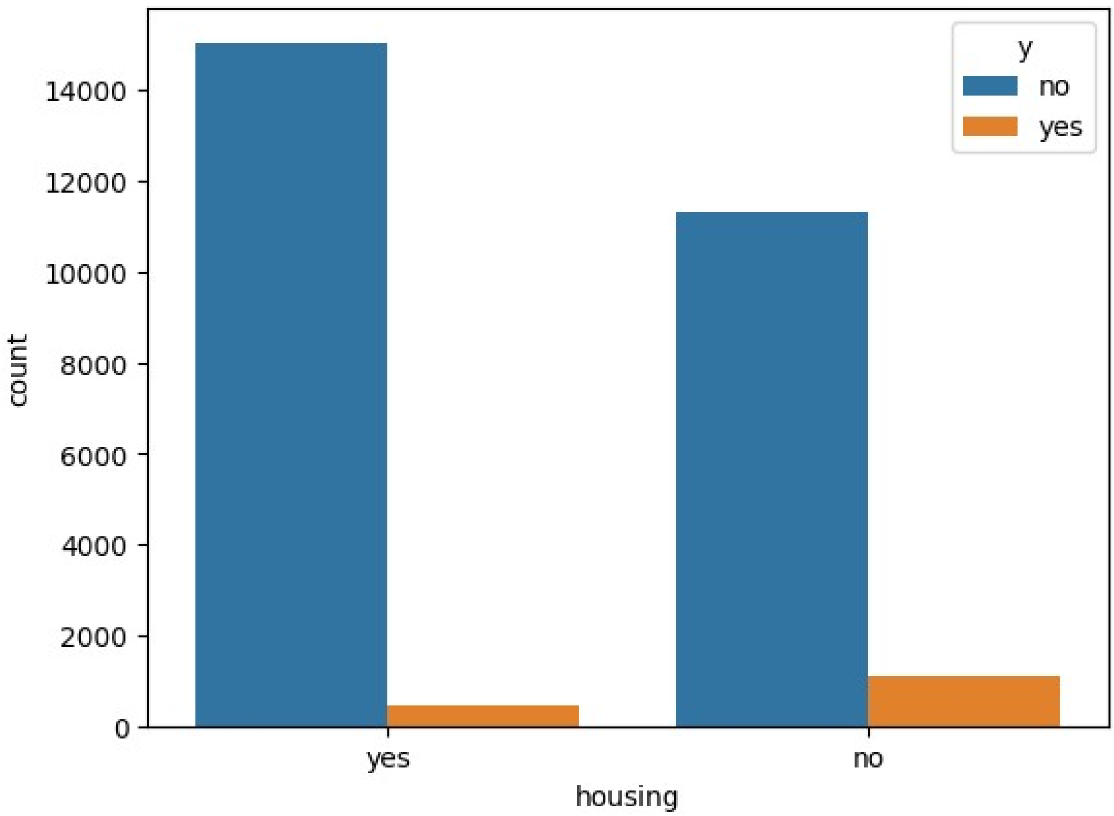
Observation: * very few clients are (default[yes])

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

```
yes    15510
no     12420
Name: housing, dtype: int64
```

```
sns.countplot(x=df['housing'],hue=df['y'])
```

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



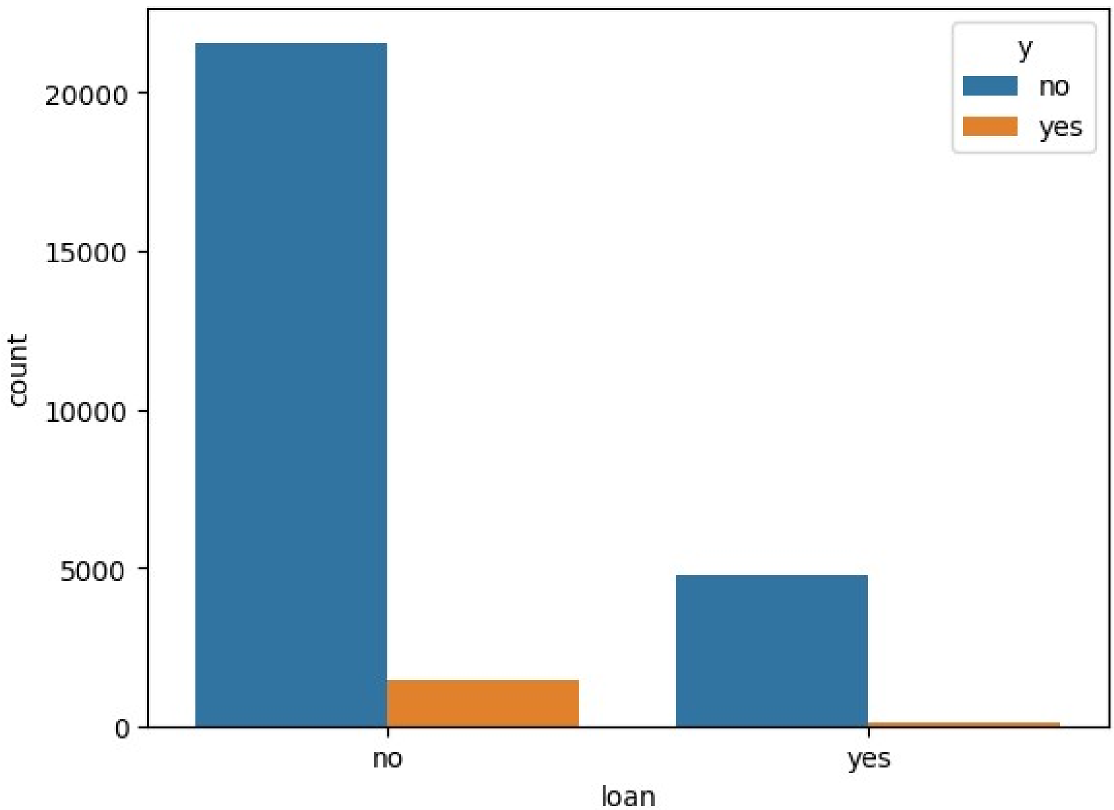
Observation: * Most of the people (housing_“yes”)

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

```
no     23003
yes     4927
Name: loan, dtype: int64
```

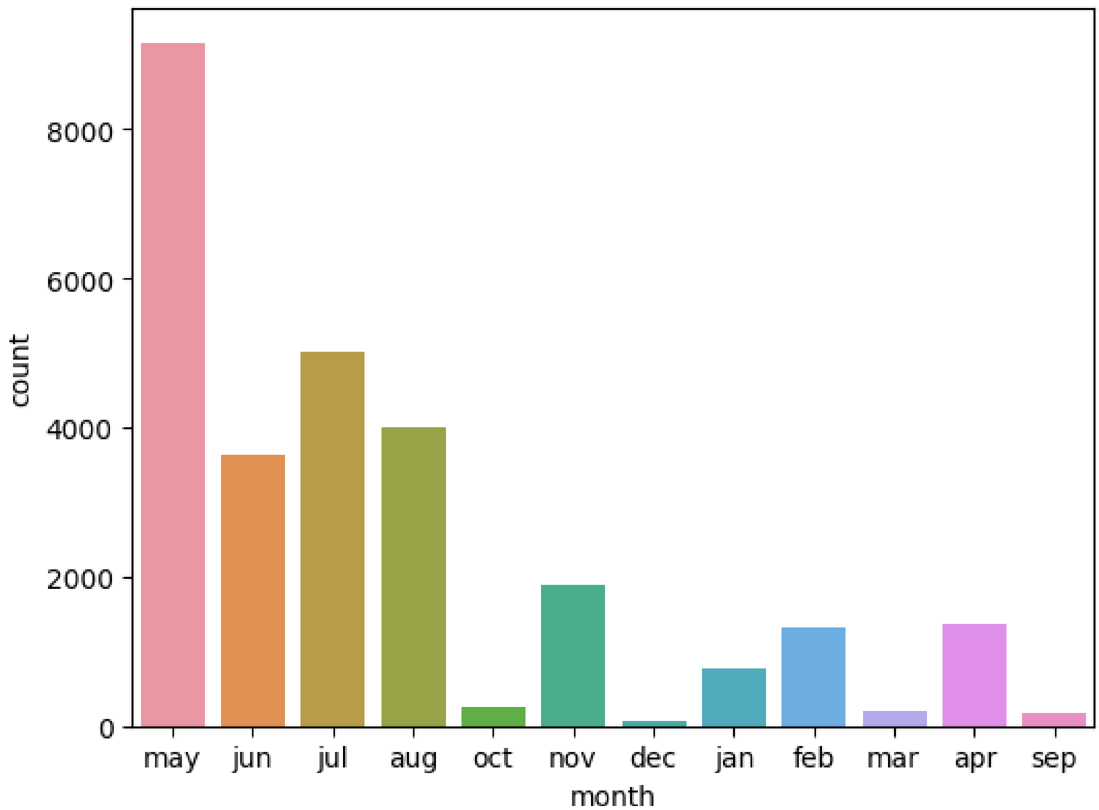
```
sns.countplot(x=df['loan'],hue=df['y'])
```

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



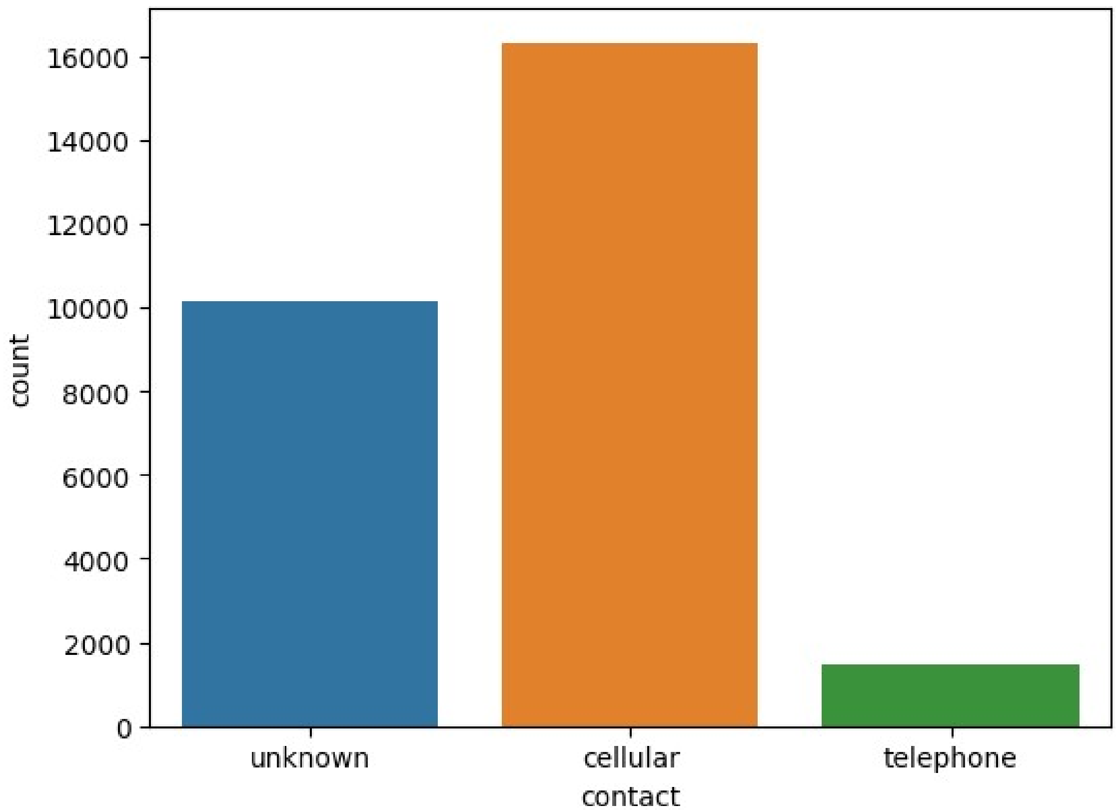

```
sns.countplot(x=df['month'])
```

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



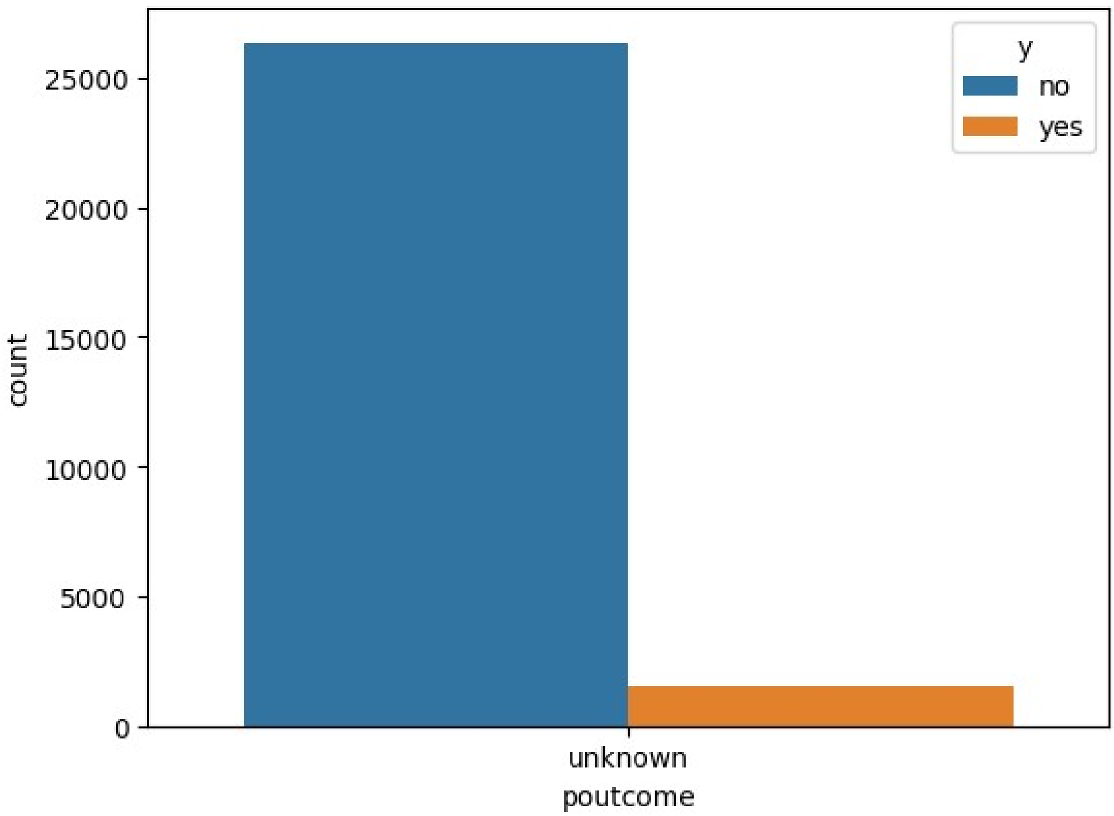

```
sns.countplot(x=df['contact'])
```

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




```
sns.countplot(x=df['poutcome'],hue=df['y'])
```

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



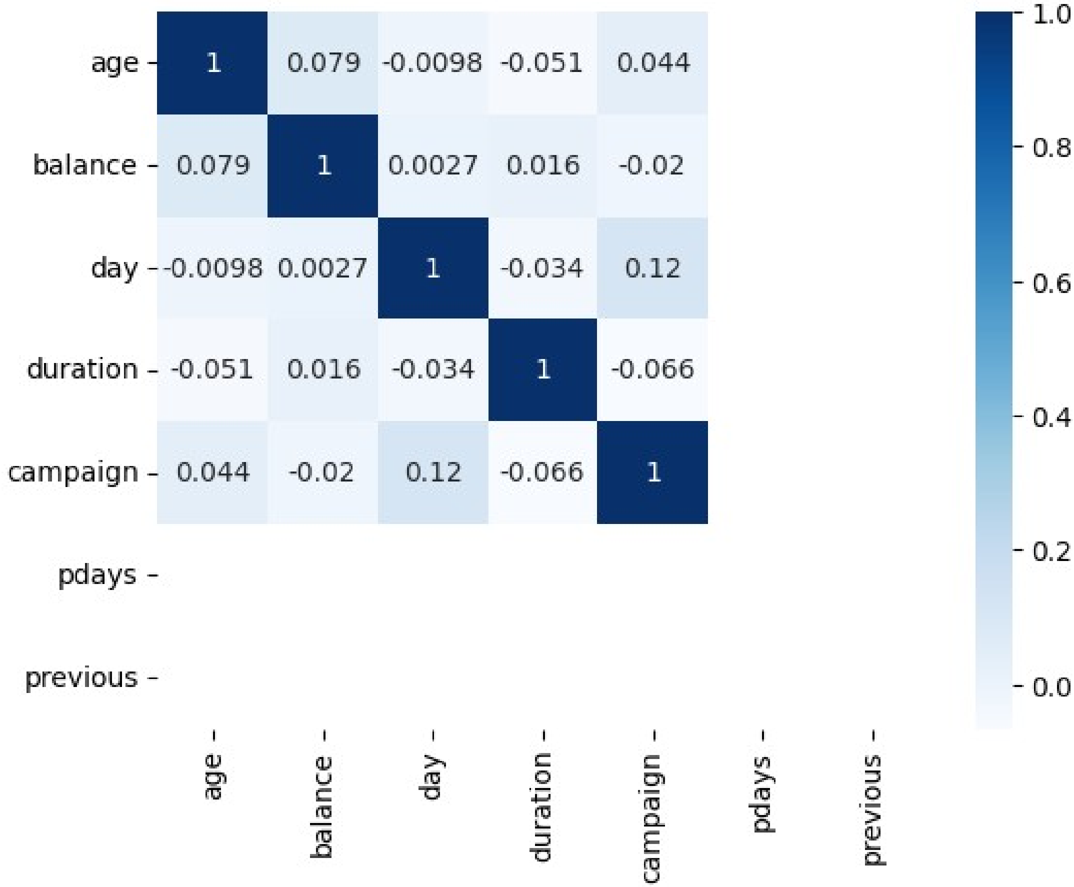
Observation: * Most of the clients contacted have previous outcome as 'unknown

```
df.head()

   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


   contact  day month  duration  campaign  pdays  previous poutcome  y
0  unknown    5   may  4.350000         1     -1         0  unknown  no
1  unknown    5   may  2.516667         1     -1         0  unknown  no
2  unknown    5   may  1.266667         1     -1         0  unknown  no
```

```
3   unknown     5    may   1.533333          1      -1          0   unknown
no
4   unknown     5    may   3.300000          1      -1          0   unknown
no
```

```
sns.heatmap(df.corr(),cmap='Blues',annot=True)
```

```
<ipython-input-69-4de9ceedb513>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  sns.heatmap(df.corr(),cmap='Blues',annot=True)

<Axes: >
```



Observation: • Over numerical features have very less correlation between them.

5 DATA ENCODER

```
print(object_data)

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

```
le=LabelEncoder()
df['y']=le.fit_transform(df['y'])
df['job']=le.fit_transform(df['job'])
df['marital']=le.fit_transform(df['marital'])
df['education']=le.fit_transform(df['education'])
df['default']=le.fit_transform(df['default'])
df['housing']=le.fit_transform(df['housing'])
df['loan']=le.fit_transform(df['loan'])
df['contact']=le.fit_transform(df['contact'])
df['month']=le.fit_transform(df['month'])
df=pd.get_dummies(df,columns=['education'])
df['poutcome']=le.fit_transform(df['poutcome'])
```

```
df
```

```
       age  job  marital  default  balance  housing  loan  contact
day  \
0       58    4        1        0     2143        1     0        2
5
1       44    9        2        0       29        1     0        2
5
2       33    2        1        0        2        1     1        2
5
3       47    1        1        0     1506        1     0        2
5
4       33   11        2        0        1        0     0        2
5
...    ...  ...      ...      ...      ...      ...   ...      ...  ..
.
45198   37    4        1        0     1428        0     0        0
16
45202   34    0        2        0      557        0     0        0
17
45203   23    8        2        0      113        0     0        0
17
45205   25    9        2        0      505        0     1        0
17
45209   57    1        1        0      668        0     0        1
17

       month  duration  campaign  pdays  previous  poutcome  y
education_0  \
0          8  4.350000         1     -1         0         0  0
0
1          8  2.516667         1     -1         0         0  0
0
2          8  1.266667         1     -1         0         0  0
0
3          8  1.533333         1     -1         0         0  0
0
```

```
4           8  3.300000         1     -1          0          0  0
0
...       ...       ...       ...    ...        ...        ... ..
...
45198       9  5.550000         2     -1          0          0  0
0
45202       9  3.733333         1     -1          0          0  1
0
45203       9  4.433333         1     -1          0          0  1
0
45205       9  6.433333         2     -1          0          0  1
0
45209       9  8.466667         4     -1          0          0  0
0

       education_1  education_2  education_3
0                0            1            0
1                1            0            0
2                1            0            0
3                0            0            1
4                0            0            1
...            ...          ...          ...
45198            0            1            0
45202            1            0            0
45203            0            1            0
45205            1            0            0
45209            1            0            0

[27930 rows x 20 columns]
```

#Features (x) and Target (y) Split:

```
x=df.drop(columns=['y'])
y=df['y']
```

6 StandardScaler

```
ssr=StandardScaler()
x=ssr.fit_transform(x)
```

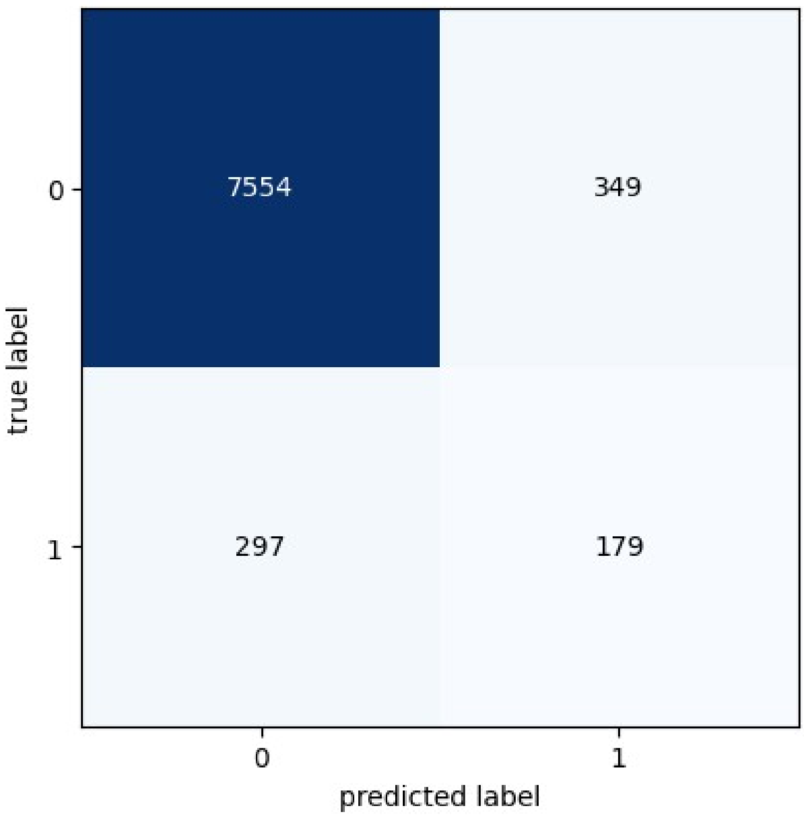
#Data split

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,rando
m_state=42)

x

array([[ 1.78693298, -0.09288467, -0.2653789 , ..., -1.05917738,
         1.61885443, -0.20248181],
```

```
       [ 0.36976714,  1.41910317,  1.37408862, ...,  0.94412893,
        -0.61772077, -0.20248181],
       [-0.74372031, -0.6976798 , -0.2653789 , ...,  0.94412893,
        -0.61772077, -0.20248181],
       ...,
       [-1.75598163,  1.1167056 ,  1.37408862, ..., -1.05917738,
         1.61885443, -0.20248181],
       [-1.55352937,  1.41910317,  1.37408862, ...,  0.94412893,
        -0.61772077, -0.20248181],
       [ 1.68570685, -1.00007737, -0.2653789 , ...,  0.94412893,
        -0.61772077, -0.20248181]])
```

#Decision Tree

```
dtc=DecisionTreeClassifier(random_state=42)
dtc.fit(x_train,y_train)
y_pred=dtc.predict(x_test)

y_pred

array([0, 0, 0, ..., 0, 1, 0])

cr=classification_report(y_test,y_pred)
print('classification_report\n',cr)
acc=accuracy_score(y_test,y_pred)*100
print('accuracy:',acc)
err=np.mean(y_pred!=y_test)*100
print('Error value',err)
cm=confusion_matrix(y_test,y_pred)
print('confusion_matrix\n',cm)

classification_report
               precision    recall  f1-score   support

           0       0.96      0.96      0.96      7903
           1       0.34      0.38      0.36       476

    accuracy                           0.92      8379
   macro avg       0.65      0.67      0.66      8379
weighted avg       0.93      0.92      0.92      8379

accuracy: 92.29024943310658
Error value 7.709750566893423
confusion_matrix
 [[7554  349]
 [ 297  179]]

plot_confusion_matrix(cm)

(<Figure size 640x480 with 1 Axes>,
 <Axes: xlabel='predicted label', ylabel='true label'>)
```


7554
349
297
179
0
1
true label
0
1
predicted label