tdp4n2mu7

December 4, 2023

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”,“blue-collar”,“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

(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

[138]:
```
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
```

[67]:
```
# Load the dataset
df=pd.read_csv('bank.csv')
```

[68]:
```
df
```

[68]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	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									

```
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)

[69]:
```
# shallow copy
df2=df.copy()
```

[70]:
```
#shape of a DataFrame.
df.shape
```

[70]:
```
(45211, 17)
```

[71]:
```
# Display all columns
df.columns
```

[71]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

[72]:
```
# displays the top rows of a DataFrame
df.head()
```

[72]:
```
   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
```

[73]:
```
#shows the bottom rows
df.tail()
```

[73]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
45206	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

[74]:
```
# specific rows of a DataFrame ( "integer location" Method)
df.iloc[100:200]
```

[74]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
100	44	blue-collar	married	secondary	no	-674	yes	no	unknown	5	may	257	1	-1	0	unknown	no
101	53	blue-collar	married	primary	no	90	no	no	unknown	5	may	124	1	-1	0	unknown	no
102	52	blue-collar	married	primary	no	128	yes	no	unknown	5	may	229	1	-1	0	unknown	no
103	59	blue-collar	married	primary	no	179	yes	no	unknown	5	may	55	3	-1	0	unknown	no
104	27	technician	single	tertiary	no	0	yes	no	unknown	5	may	400	1	-1	0	unknown	no
..	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
195	33	blue-collar	single	secondary	no	307	yes	no	unknown	5	may	309	2	-1	0	unknown	no
196	38	services	married	secondary	no	155	yes	no	unknown	5	may	248	1	-1	0	unknown	no
197	50	technician	divorced	tertiary	no	173	no	yes	unknown	5	may	98	1	-1	0	unknown	no
198	43	management	married	tertiary	no	400	yes	no	unknown	5	may	256	1	-1	0	unknown	no
199	61	blue-collar	divorced	primary	no	1428	yes	no	unknown	5	may	82	2	-1	0	unknown	no

[100 rows x 17 columns]

[75]:
```
# 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
```

[76]:
```
# Display summary statistics for numerical columns in  DataFrame.
df.describe().T
```

[76]:

	count	mean	std	min	25%	50%	75%	max
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.0	95.0
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.0	102127.0
day	45211.0	15.806419	8.322476	1.0	8.0	16.0	21.0	31.0
duration	45211.0	258.163080	257.527812	0.0	103.0	180.0	319.0	4918.0
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.0	63.0
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.0	871.0
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.0	

```
previous     275.0
```

[77]:
```
# Dispaly (string) columns in the summary statistics.
df.describe(include=object)
```

[77]:
```
                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
```

[78]:
```
# numerical columns list
numerical_data=df.select_dtypes(include=['int64','float64']).columns.to_list()
numerical_data
```

[78]:
```
['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous']
```

[79]:
```
# 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

[80]:
```
# To check for duplicate values in a DataFrame
df.duplicated().sum()
```

[80]:
```
0
```

[81]:
```
# The number of missing values in the dataset.
df.isnull().sum()
```

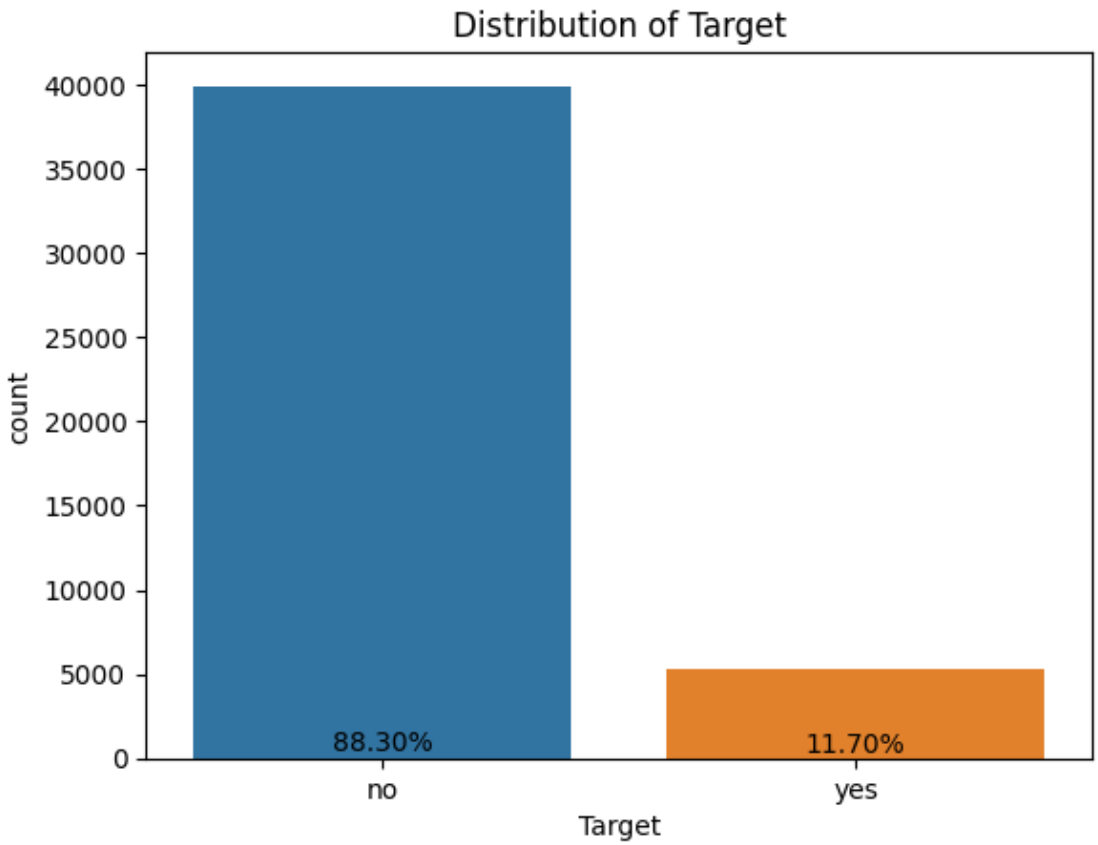
[81]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
```

```
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

[82]:
```
#Observation: Our dataset do not have any null/nan/missing values.
```

3 visualization

[83]:
```
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
```



[84]:
```
# Observation: dataset is highly imbalanced.
```

4 Outliers

[85]:
```
# 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()
```

[85]:

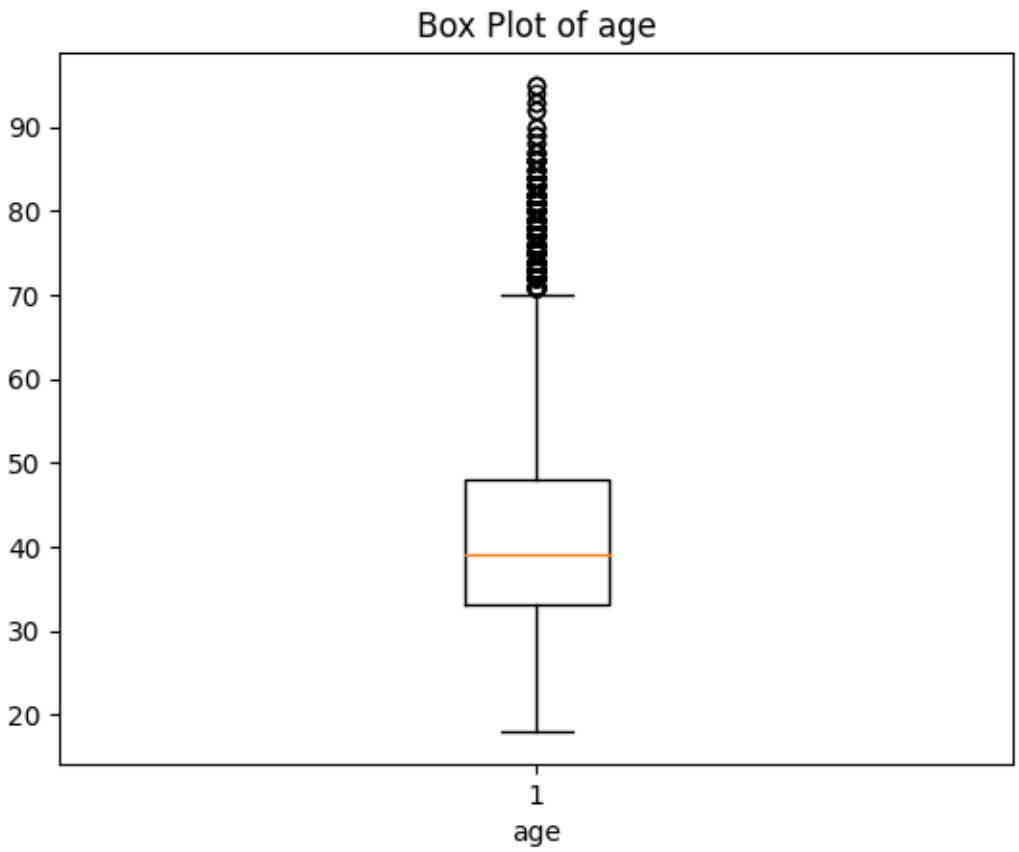
	age	balance	day	duration	campaign	\
count	44724.000000	40482.000000	45211.000000	41976.000000	42147.000000	
mean	40.545524	640.636233	15.806419	203.490947	2.129950	
std	9.978232	844.435442	8.322476	140.805074	1.315842	

```
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
```

[86]:
```
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
```

[87]:
```
plt.boxplot(x=df['age'])
plt.xlabel('age')
plt.title('Box Plot of age')
```

[87]:
```
Text(0.5, 1.0, 'Box Plot of age')
```

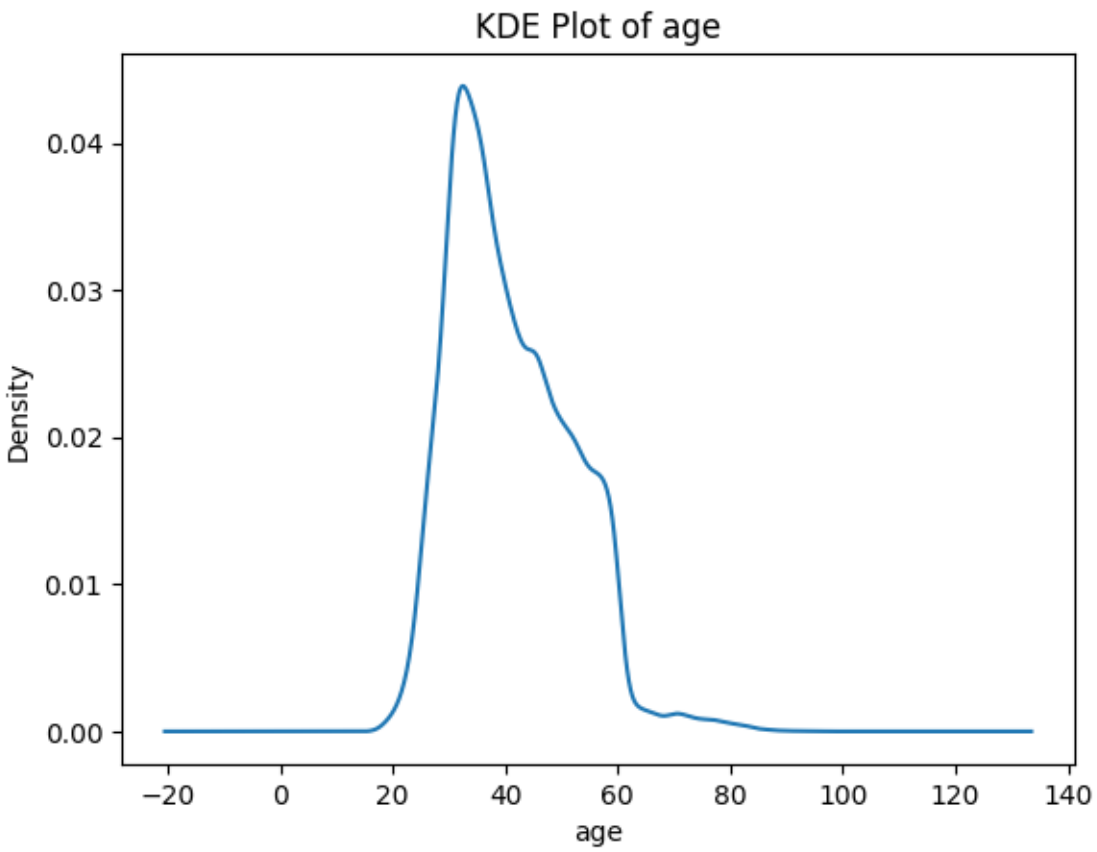


[88]:
```
df['age'].describe()
```

[88]:
```
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
```

[89]:
```
df['age'].plot.kde()
plt.xlabel('age')
plt.title('KDE Plot of age')
```

[89]:
```
Text(0.5, 1.0, 'KDE Plot of age')
```



[90]:
```
df.shape
```

[90]:
```
(45211, 17)
```

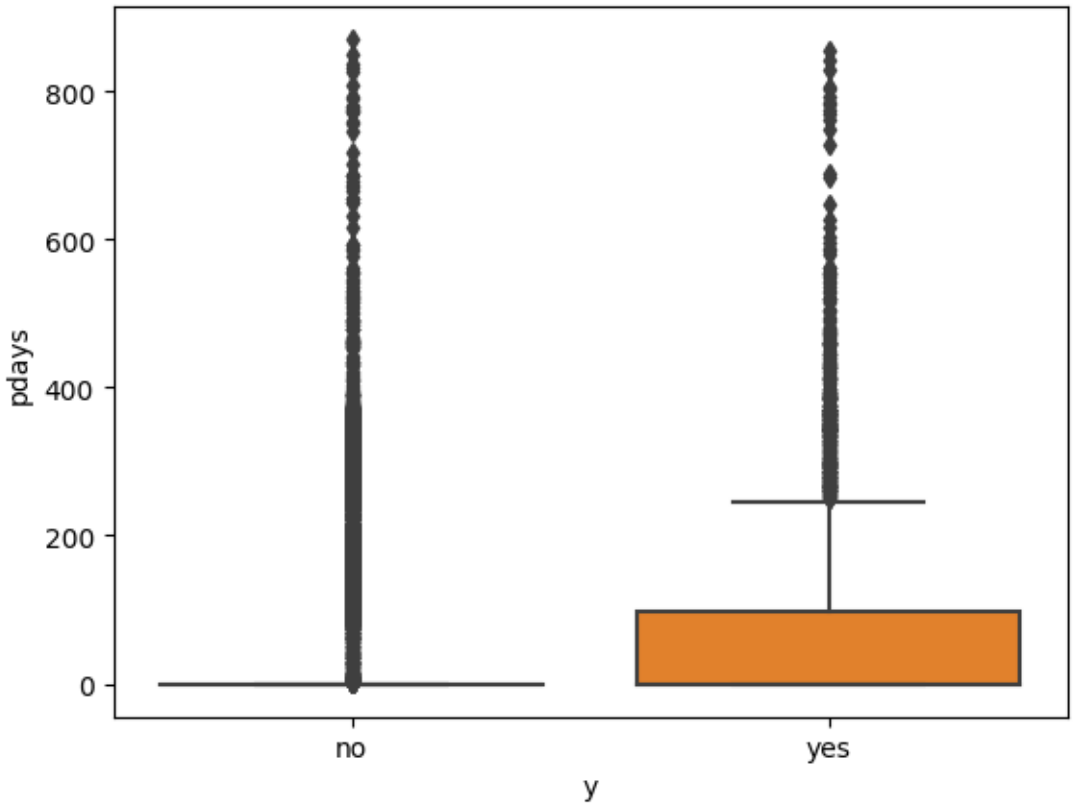
[91]:
```
# Remove outliers
df=remove_outliers(df,'age')
df['age'].describe()
```

[91]:
```
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
```

Observation: * There are outliers (age) as we can see from boxplot. * after outlier maximum age of 70

[92]:
```
sns.boxplot(y=df['pdays'],x=df['y'])
```

[92]:
```
<Axes: xlabel='y', ylabel='pdays'>
```



[93]:
```
df['pdays'].describe()
```

[93]:
```
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
```

[94]:
```
# Remove outliers
df=remove_outliers(df,'pdays')
```

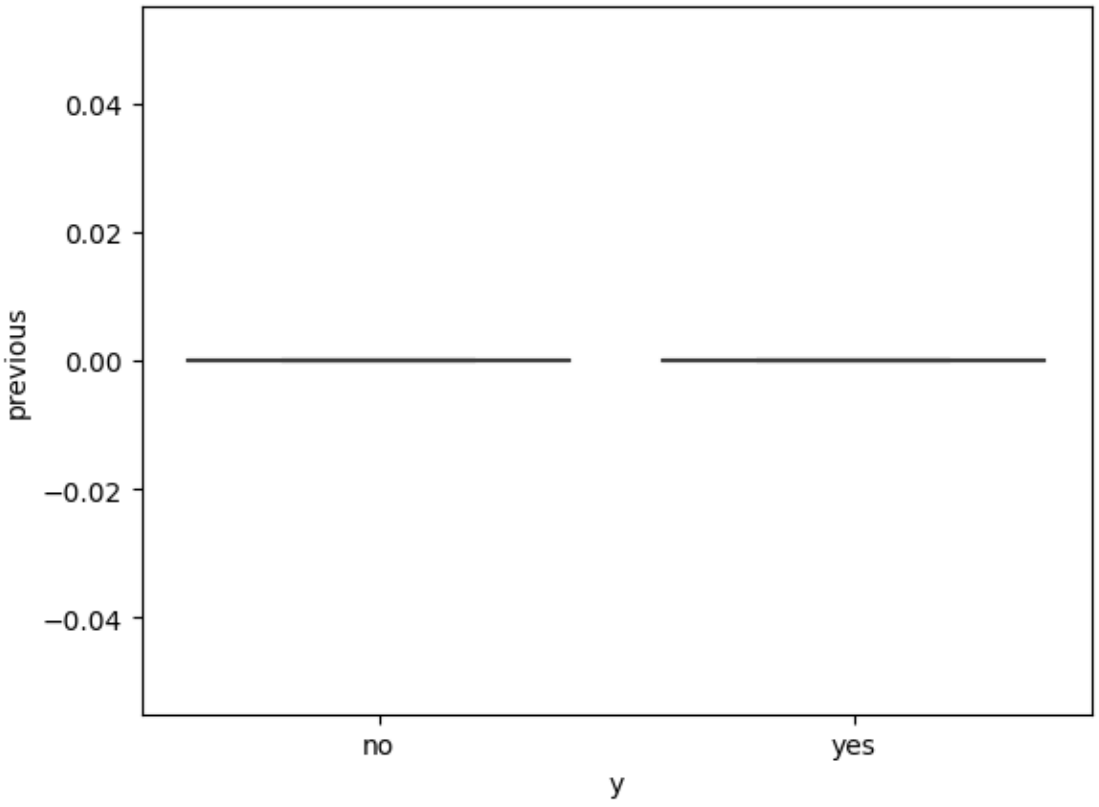
[95]:
```
df['pdays'].describe()
```

[95]:
```
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

[96]:
```
sns.boxplot(y=df['previous'],x=df['y'])
```

[96]:
```
<Axes: xlabel='y', ylabel='previous'>
```



[97]:
```
df['previous'].describe()
```

[97]:
```
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
```

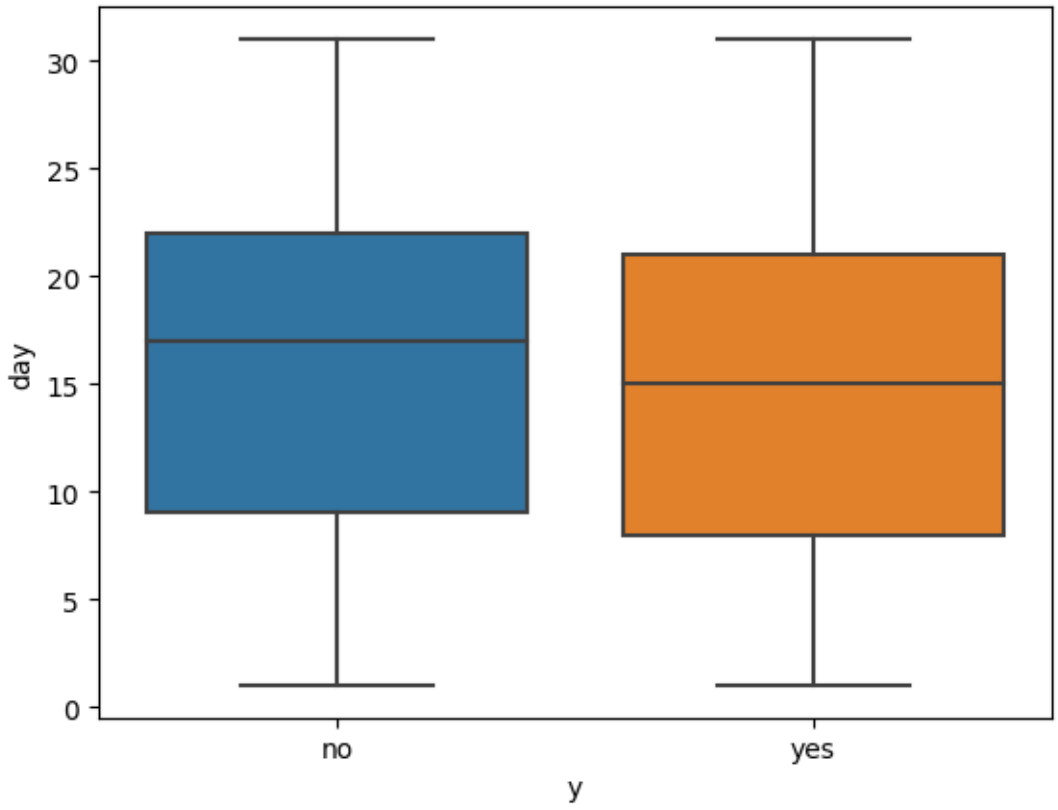
[98]:
```
# Remove outliers
df=remove_outliers(df,'previous')
df['previous'].describe()
```

[98]:
```
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

[99]:
```
sns.boxplot(y=df['day'],x=df['y'])
```

[99]:
```
<Axes: xlabel='y', ylabel='day'>
```



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

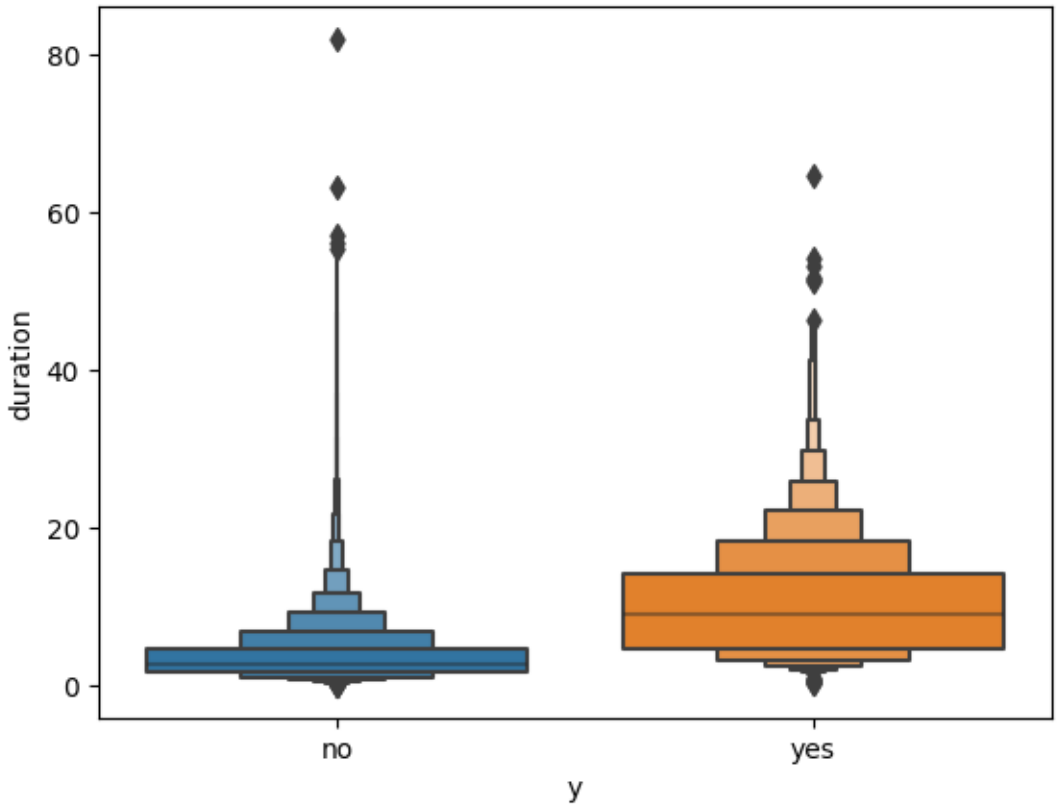
[100]:
```
# converting call duration from seconds to minute
df['duration'] = df['duration']/60
```

[101]:
```
df['duration'].describe()
```

[101]:
```
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
```

[102]:
```
sns.boxenplot(y=df['duration'],x=df['y'])
```

[102]:
```
<Axes: xlabel='y', ylabel='duration'>
```



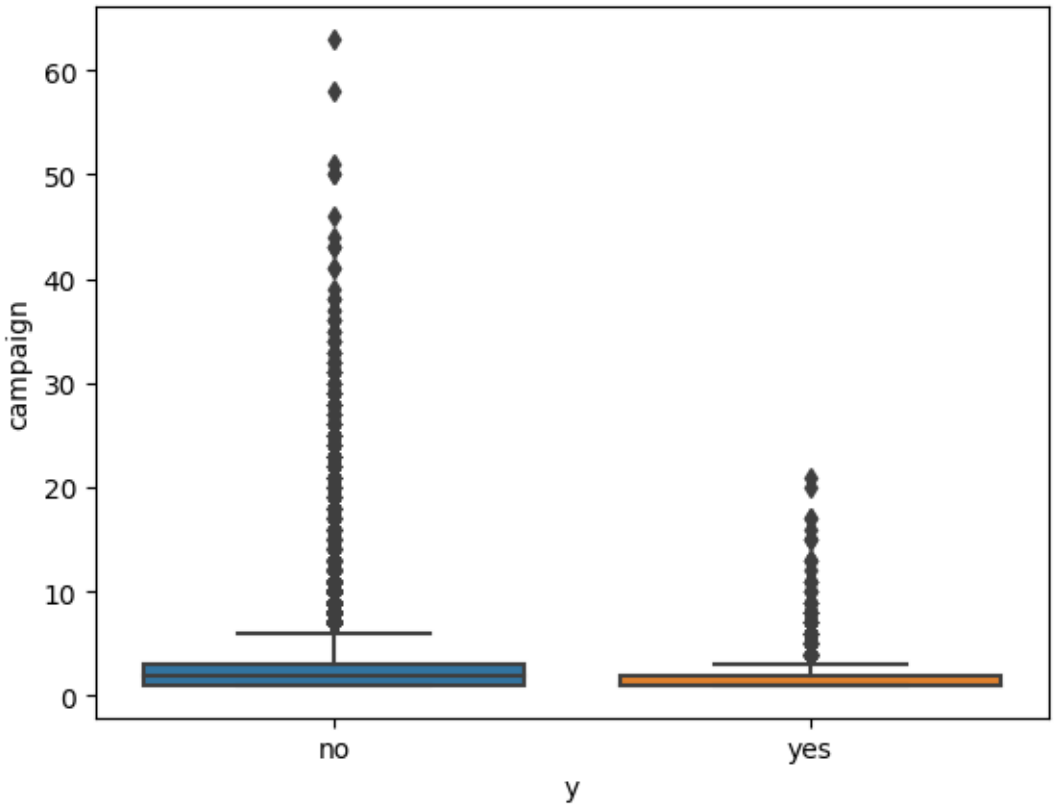
[103]:
```
# Remove outliers
df=remove_outliers(df,'duration')
df['duration'].describe()
```

[103]:
```
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

[104]:
```
sns.boxplot(y=df['campaign'],x=df['y'])
```

[104]:
```
<Axes: xlabel='y', ylabel='campaign'>
```



[105]:
```
df['campaign'].describe()
```

[105]:
```
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
```

[106]:
```
# Remove outliers
df=remove_outliers(df,'campaign')
df['campaign'].describe()
```

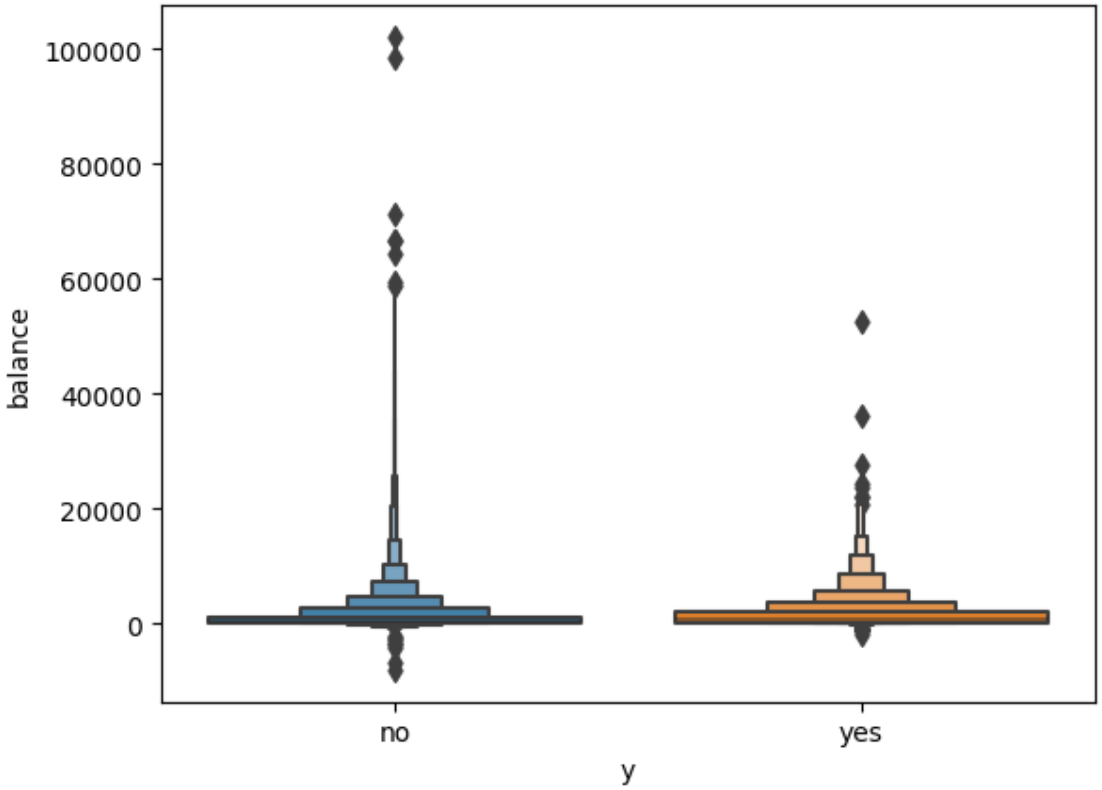
[106]:
```
count    31275.000000
mean         2.185995
std          1.341735
min          1.000000
25%          1.000000
```

```
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

[107]:
```
sns.boxenplot(x=df['y'],y=df['balance'])
```

[107]:
```
<Axes: xlabel='y', ylabel='balance'>
```



[108]:
```
df['balance'].describe()
```

[108]:
```
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
```

[109]:
```
# Remove outliers
df=remove_outliers(df,'balance')
df['balance'].describe()
```

[109]:
```
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

[110]:
```
df.isnull().sum()
```

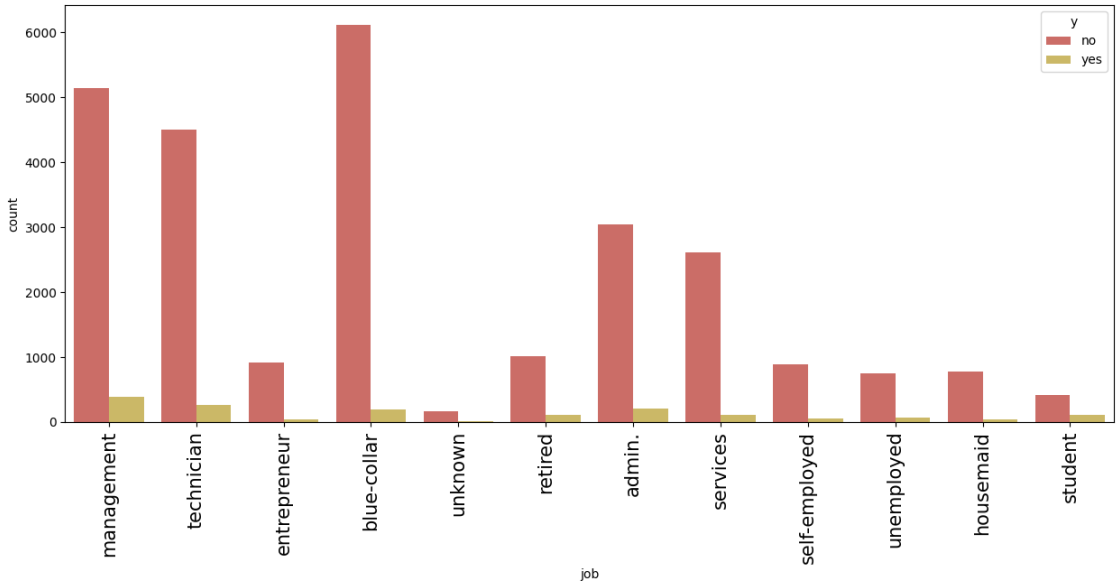
[110]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

[111]:
```
object_data
```

[111]:
```
['job',
 'marital',
 'education',
 'default',
 'housing',
```

```
 'loan',
 'contact',
 'month',
 'poutcome',
 'y']
```

[112]:
```
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()
```



[113]:
```
jobs
```

[113]:
```
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
```

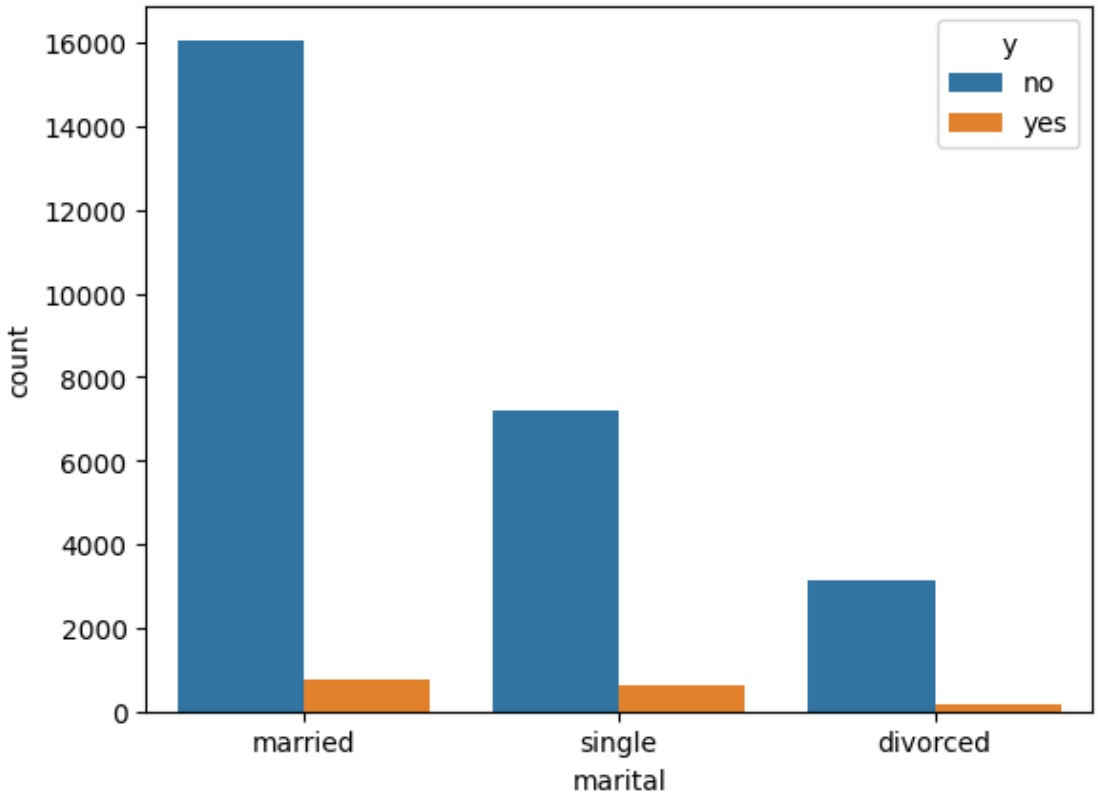
Observation: * Top contacted clients are from job type: 'blue-collar', 'management' & 'technician'

[114]:
```
df['marital'].value_counts()
```

[114]:
```
married     16807
single       7822
divorced     3301
Name: marital, dtype: int64
```

[115]:
```
sns.countplot(x=df['marital'],hue=df['y'])
```

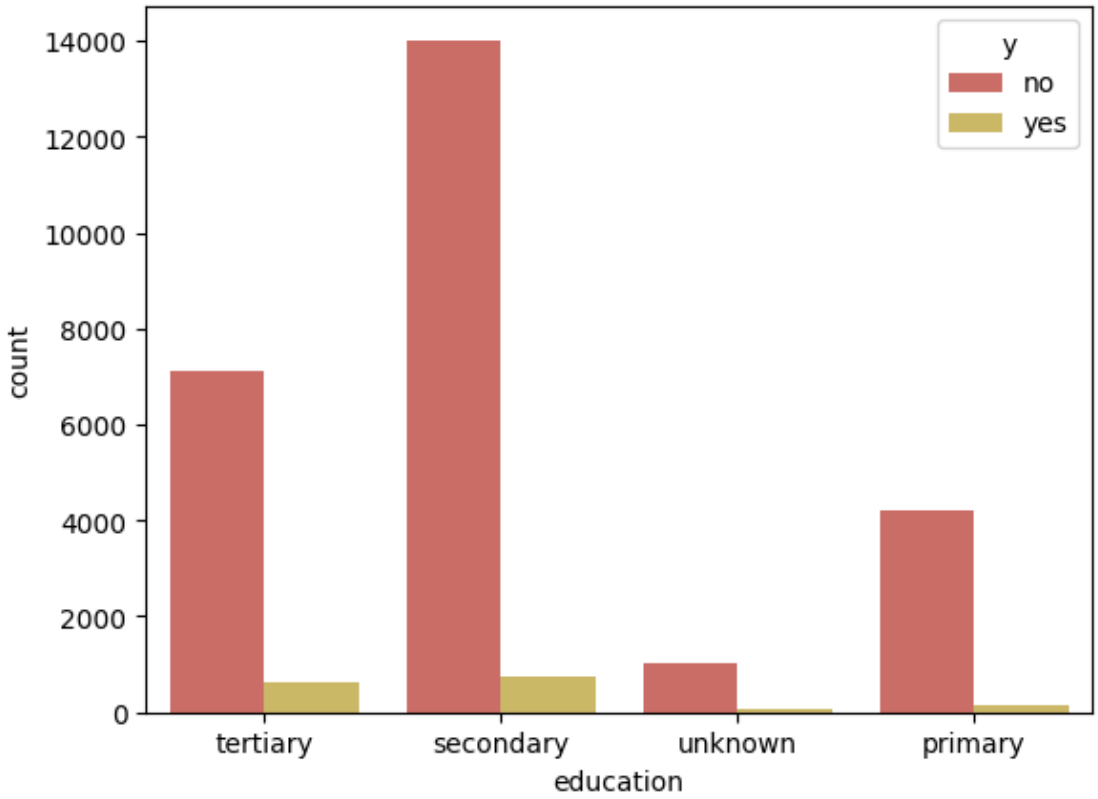
[115]:
```
<Axes: xlabel='marital', ylabel='count'>
```



Observation: * Top client married

[116]:
```
sns.countplot(x=df['education'],hue=df['y'],palette=sns.color_palette("hls", 8))
```

[116]:
```
<Axes: xlabel='education', ylabel='count'>
```



Observation

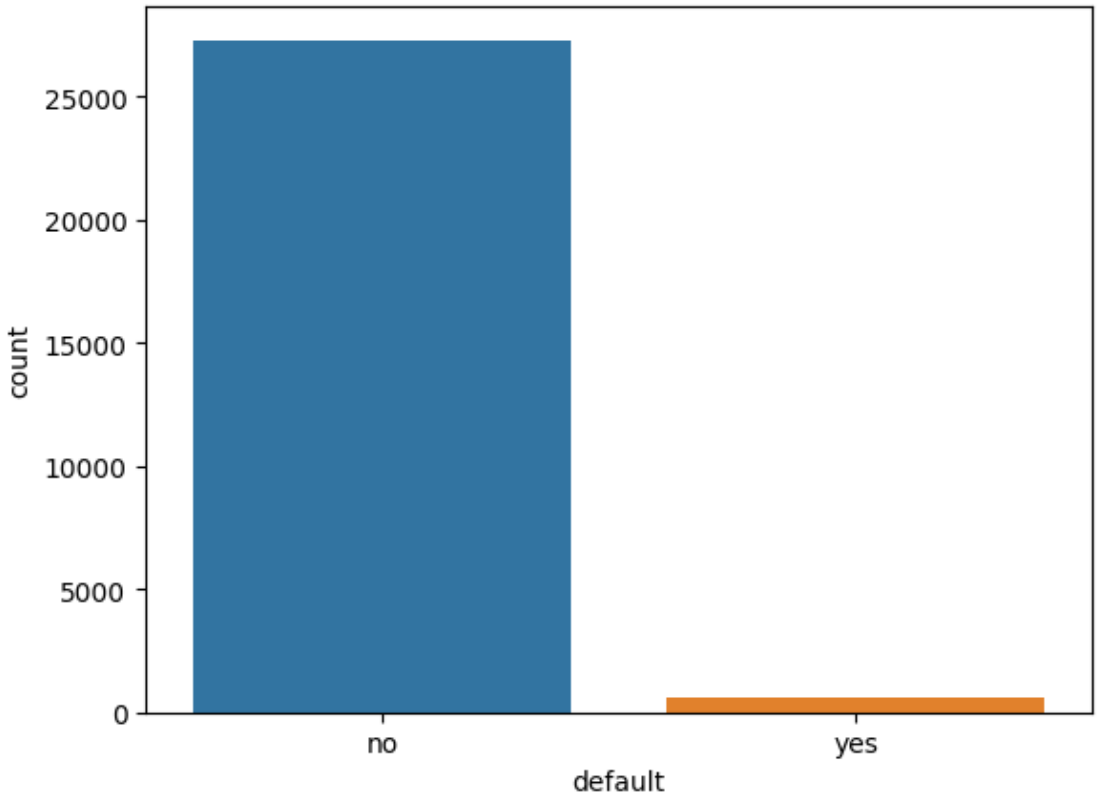
- Most of the people who are contacted have secondary or tertiray education.

[117]:
```
df['default'].value_counts()
```

[117]:
```
no      27304
yes       626
Name: default, dtype: int64
```

[118]:
```
sns.countplot(x=df['default'])
```

[118]:
```
<Axes: xlabel='default', ylabel='count'>
```



[119]:
```
df[df['default'] == 'yes'].y.count()
```

[119]:
```
626
```

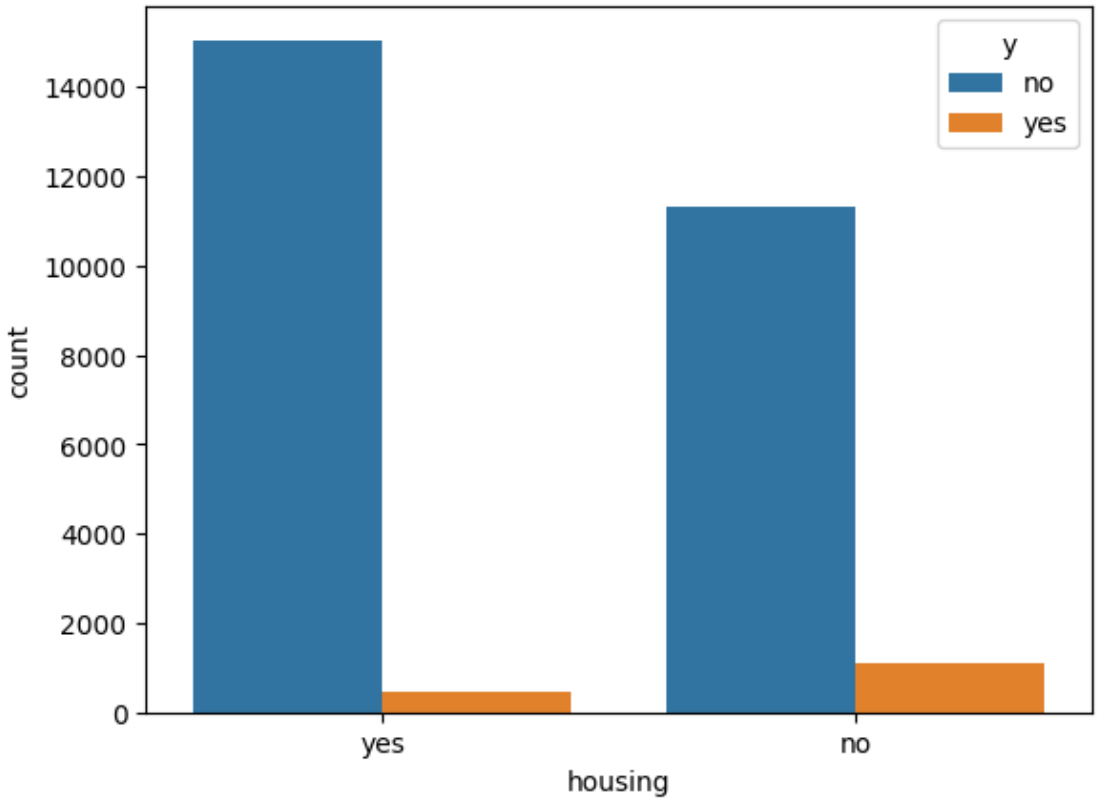
Observation: * very few clients are (default[yes])

[120]:
```
df['housing'].value_counts()
```

[120]:
```
yes    15510
no     12420
Name: housing, dtype: int64
```

[121]:
```
sns.countplot(x=df['housing'],hue=df['y'])
```

[121]:
```
<Axes: xlabel='housing', ylabel='count'>
```



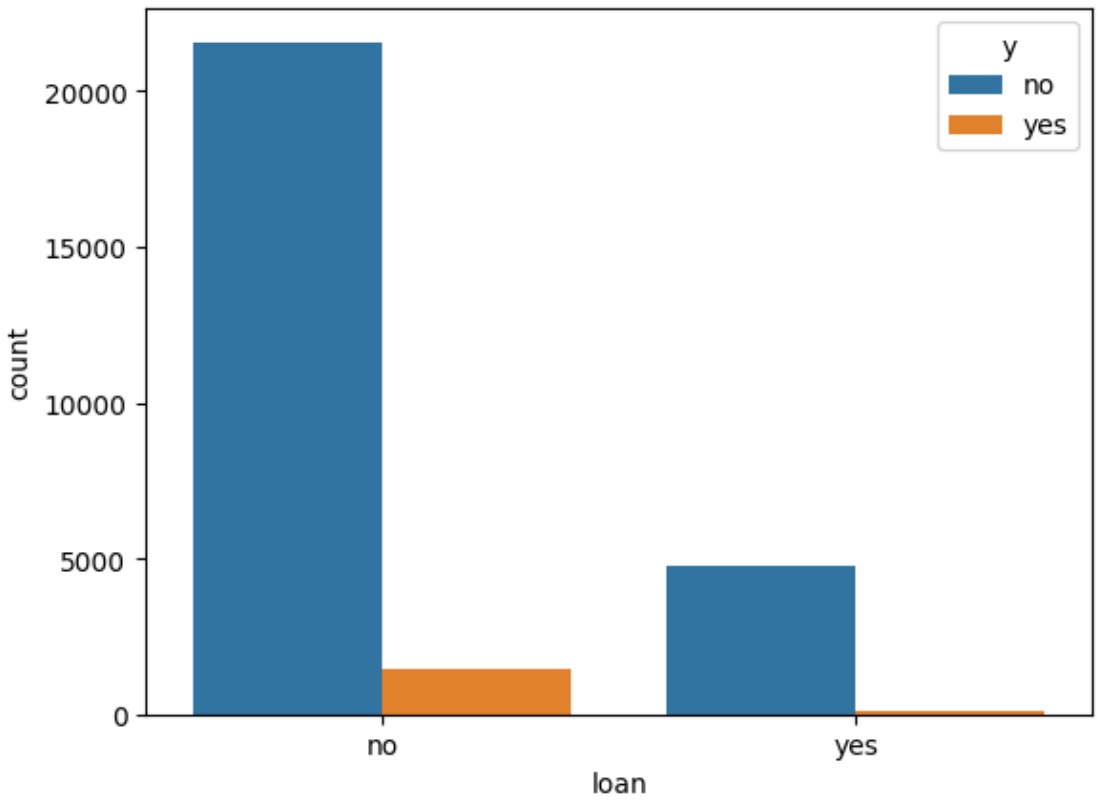
Observation: * Most of the people (housing_"yes")

[122]:
```
df['loan'].value_counts()
```

[122]:
```
no     23003
yes     4927
Name: loan, dtype: int64
```

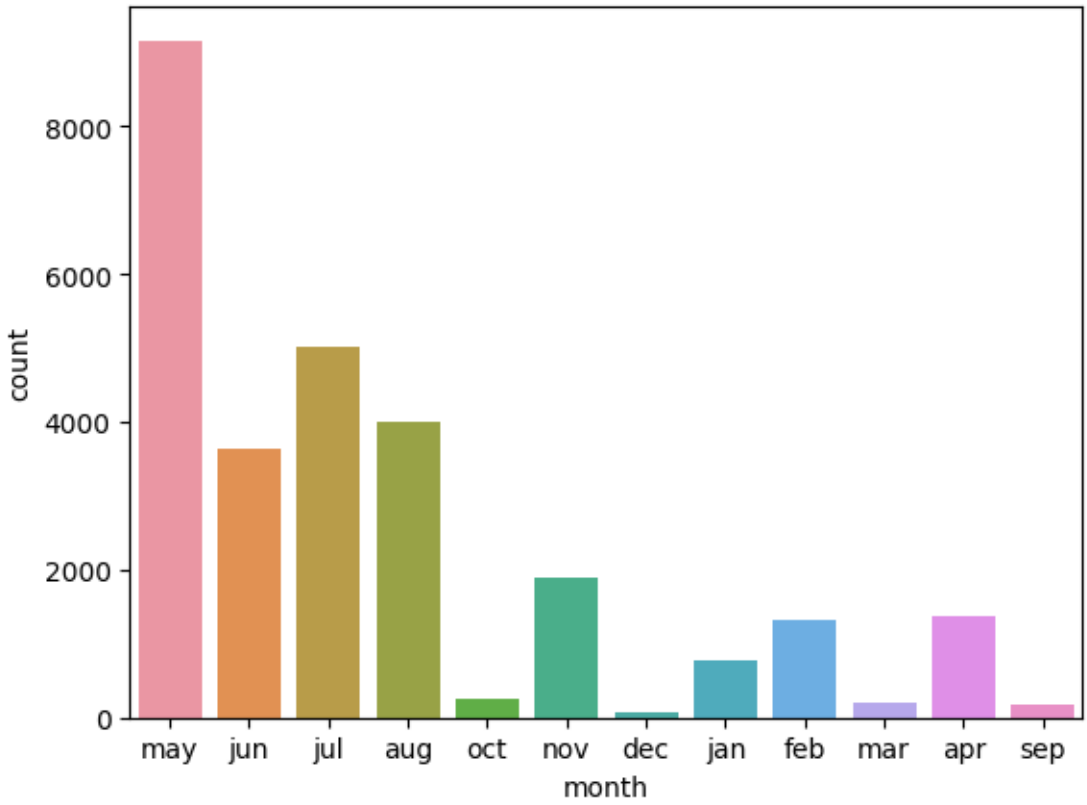
[123]:
```
sns.countplot(x=df['loan'],hue=df['y'])
```

[123]:
```
<Axes: xlabel='loan', ylabel='count'>
```



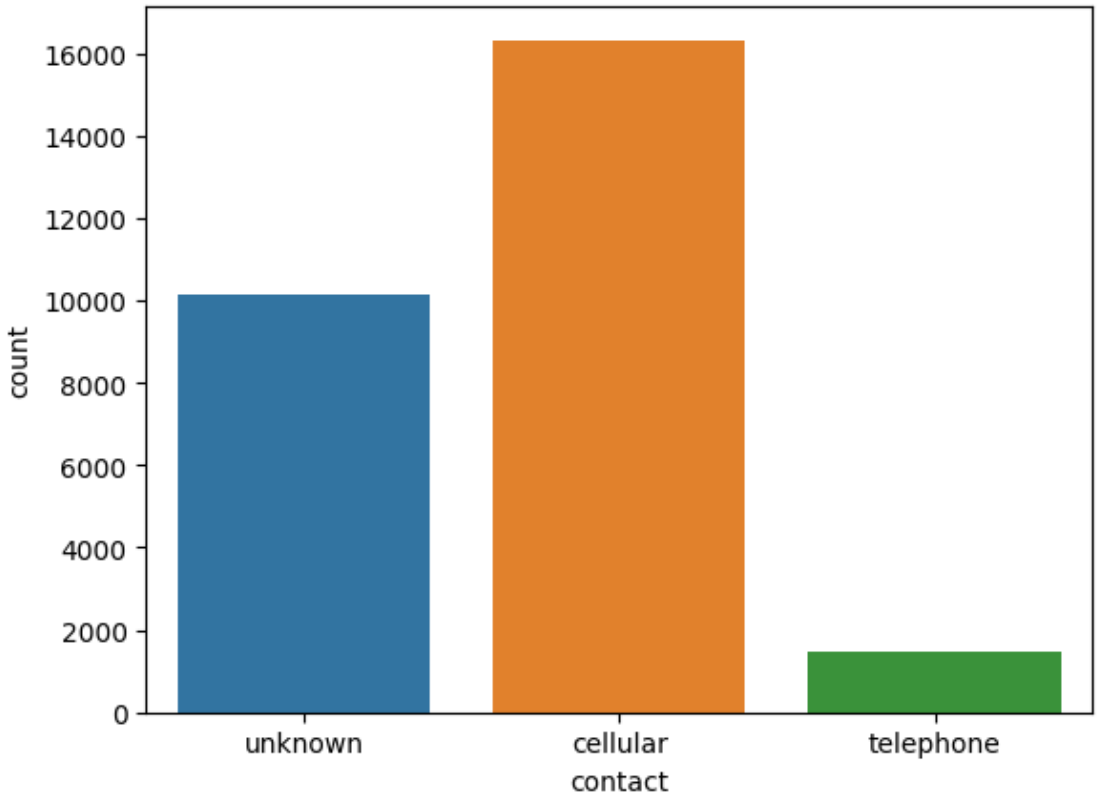
[124]:
```
sns.countplot(x=df['month'])
```

[124]:
```
<Axes: xlabel='month', ylabel='count'>
```



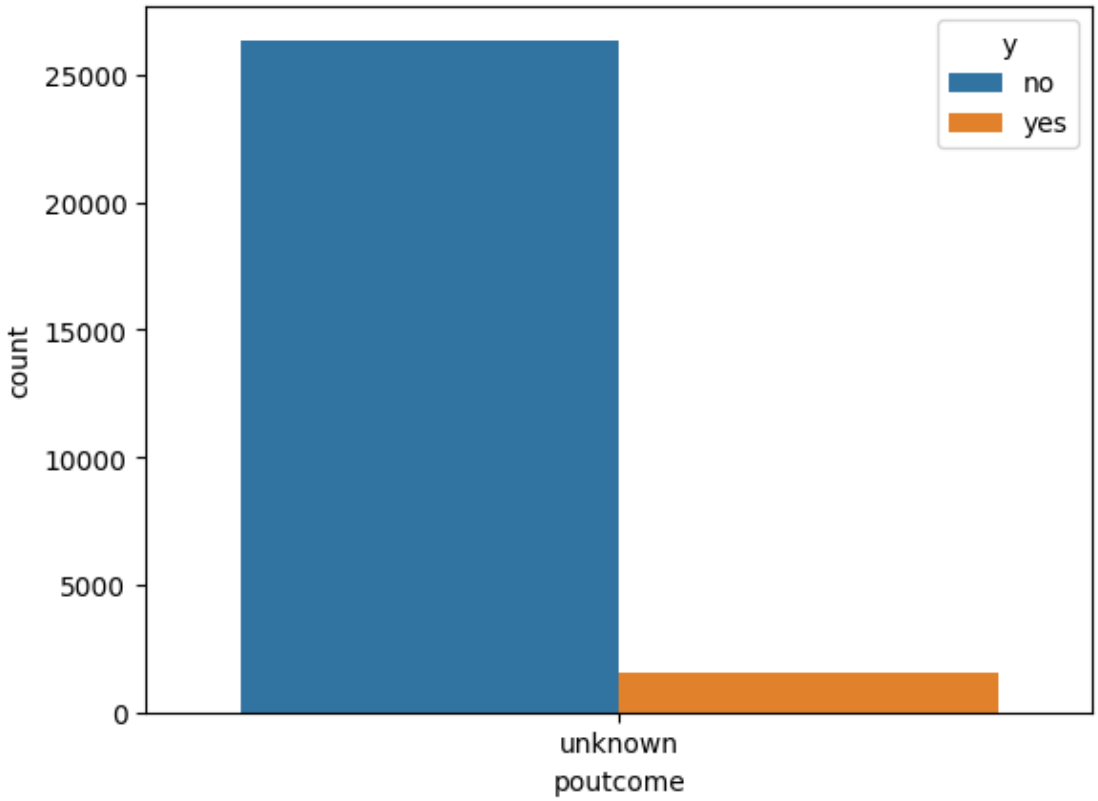
[125]:
```
sns.countplot(x=df['contact'])
```

[125]:
```
<Axes: xlabel='contact', ylabel='count'>
```



[126]:
```
sns.countplot(x=df['poutcome'],hue=df['y'])
```

[126]:
```
<Axes: xlabel='poutcome', ylabel='count'>
```



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

[127]:
```
df.head()
```

[127]:

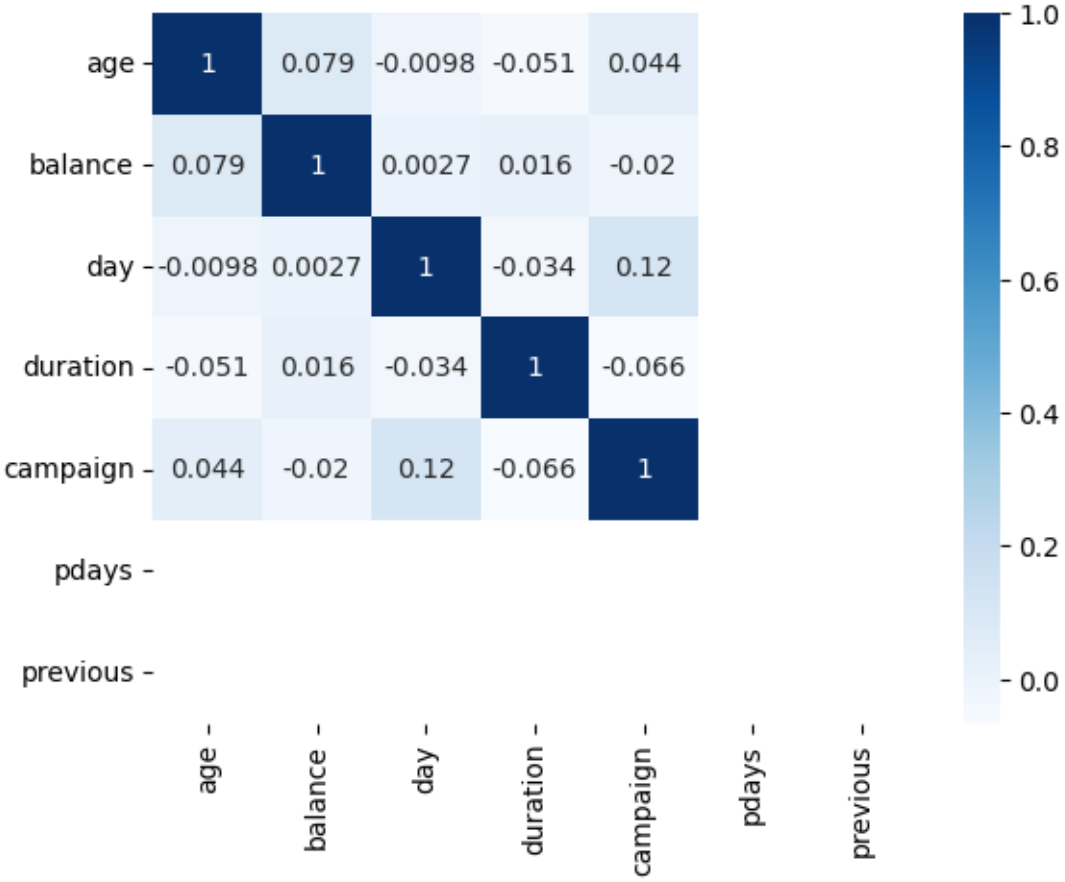
	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	4.350000	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	2.516667	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1.266667	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1.533333	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	3.300000	1	-1	0	unknown	no

[128]:
```
sns.heatmap(df.corr(),cmap='Blues',annot=True)
```

```
<ipython-input-128-4de9ceedb513>: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)
```

[128]: <Axes: >



Observation:

- Over numerical features have very less correlation between them.

5 DATA ENCODER

[129]:
```
print(object_data)
```

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

[130]:
```
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'])
```

[131]:
```
df
```

[131]:

	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:

[132]:
```
x=df.drop(columns=['y'])
y=df['y']
```

6 StandardScaler

[133]:
```
ssr=StandardScaler()
x=ssr.fit_transform(x)
```

#Data split

[134]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3␣
↪,random_state=42)
```

[135]:
```
x
```

[135]:
```
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

[136]:
```
dtc=DecisionTreeClassifier(random_state=42)
dtc.fit(x_train,y_train)
y_pred=dtc.predict(x_test)
```

[137]:
```
y_pred
```

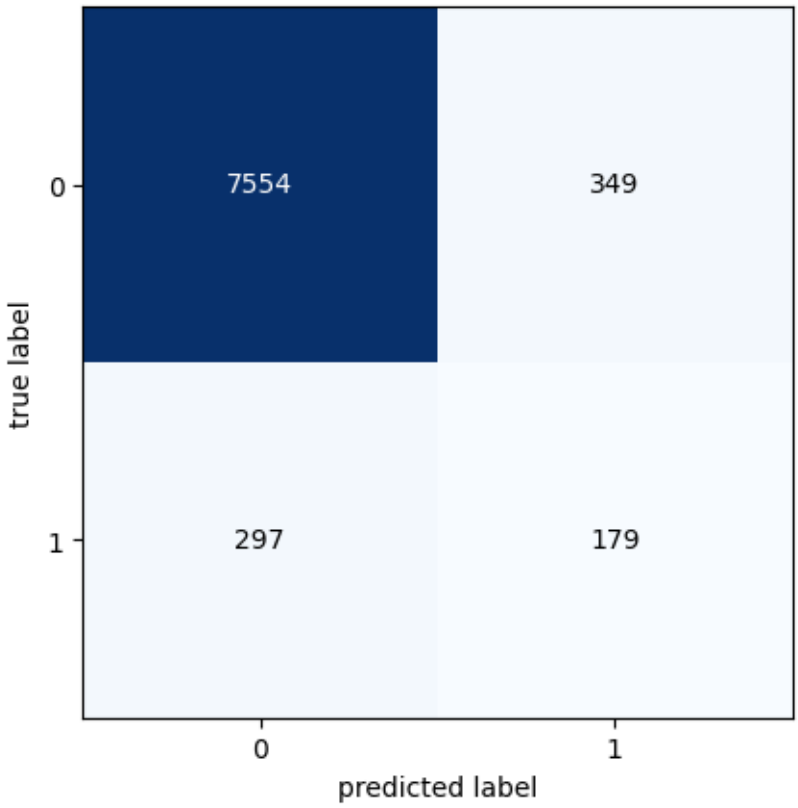
[137]:
```
array([0, 0, 0, …, 0, 1, 0])
```

[139]:
```
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]]
```

[140]:
```
plot_confusion_matrix(cm)
```

[140]:
```
(<Figure size 640x480 with 1 Axes>,
 <Axes: xlabel='predicted label', ylabel='true label'>)
```



[ ]:
```
plt.figure(figsize=(18,16))
tree.plot_tree(dtc)
sns.despine()
```

[ ]:
```

```