TERM DEPOSIT PREDICTION

A Machine Learning Project to predict if a client will subscribe (yes/no) to a term deposit.

In this project I will demonstrate how to build a model, to predict which clients will subscribing to a term deposit, with inception of machine learning. In the first part we will deal with the description and visualization of the analysed data, and in the second we will go to data classification models.

features

- age : age (numeric)
- job : type of job
- marital : marital status
- education : education
- default: has credit in default?
- balance in bank account
- housing: has housing loan?
- loan: has personal loan?
- day_of_week: last contact day of the week
- month: last contact month of year
- duration: last contact duration, in seconds
- campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- pdays: number of days that passed by after the client was last contacted from a previous campaign
- previous: number of contacts performed before this campaign and for this client
- y : outcome of the previous marketing y - has the client subscribed a term deposit?

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv('/content/dataset_project.csv (1).csv')
df
```

```
          age           job   marital  education default  balance
housing loan  \
0      999.0    management   married   tertiary      no   2143.0
yes   no
1       44.0    technician    single  secondary      no     29.0
yes   no
2       33.0  entrepreneur   married  secondary      no      2.0
yes  yes
3       47.0   blue-collar   married    unknown      no   1506.0
yes   no
4       33.0       unknown    single    unknown      no      1.0
no   no
...      ...           ...       ...        ...     ...      ...      .
..  ...
45206   51.0    technician   married   tertiary      no    825.0
no   no
45207   71.0       retired  divorced    primary      no   1729.0
no   no
45208   72.0       retired   married  secondary      no   5715.0
no   no
45209   57.0   blue-collar   married  secondary      no    668.0
no   no
45210   37.0  entrepreneur   married  secondary      no   2971.0
no   no

       day month  duration  campaign  pdays  previous    y
0        5   may       261         1     -1         0   no
1        5   may       151         1     -1         0   no
2        5   may        76         1     -1         0   no
3        5   may        92         1     -1         0   no
4        5   may       198         1     -1         0   no
...    ...   ...       ...       ...    ...       ...  ...
45206   17   nov       977         3     -1         0  yes
45207   17   nov       456         2     -1         0  yes
45208   17   nov      1127         5    184         3  yes
45209   17   nov       508         4     -1         0   no
45210   17   nov       361         2    188        11   no

[45211 rows x 15 columns]
```

```
df.head()
```

```
     age           job  marital  education default  balance housing
loan  day  \
0  999.0    management  married   tertiary      no   2143.0     yes
no    5
1   44.0    technician   single  secondary      no     29.0     yes
no    5
2   33.0  entrepreneur  married  secondary      no      2.0     yes
yes    5
```

```
3   47.0   blue-collar  married    unknown      no   1506.0     yes
no    5
4   33.0       unknown   single    unknown      no      1.0      no
no    5

  month  duration  campaign  pdays  previous   y
0   may       261         1     -1         0  no
1   may       151         1     -1         0  no
2   may        76         1     -1         0  no
3   may        92         1     -1         0  no
4   may       198         1     -1         0  no
```

```
df.tail()
```

```
        age           job   marital  education default  balance
housing loan  \
45206  51.0    technician   married   tertiary      no    825.0
no   no
45207  71.0       retired  divorced    primary      no   1729.0
no   no
45208  72.0       retired   married  secondary      no   5715.0
no   no
45209  57.0   blue-collar   married  secondary      no    668.0
no   no
45210  37.0  entrepreneur   married  secondary      no   2971.0
no   no

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

```
df.shape
```

```
(45211, 15)
```

```
df.dtypes
```

```
age          float64
job           object
marital       object
education     object
default       object
balance      float64
housing       object
loan          object
day            int64
month         object
duration       int64
```

```
campaign       int64
pdays          int64
previous       int64
y             object
dtype: object
```

```
df.describe()
```

```
                age        balance           day      duration
campaign  \
count  45202.000000   45208.000000  45211.000000  45211.000000
45211.000000
mean      40.954714    1362.346620     15.806419    258.163080
2.763841
std       11.539144    3044.852387      8.322476    257.527812
3.098021
min       -1.000000   -8019.000000      1.000000      0.000000
1.000000
25%       33.000000      72.000000      8.000000    103.000000
1.000000
50%       39.000000     448.000000     16.000000    180.000000
2.000000
75%       48.000000    1428.000000     21.000000    319.000000
3.000000
max      999.000000  102127.000000     31.000000   4918.000000
63.000000

              pdays      previous
count  45211.000000  45211.000000
mean      40.197828      0.580323
std      100.128746      2.303441
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       -1.000000      0.000000
max      871.000000    275.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 15 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45202 non-null  float64
 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    45208 non-null  float64
```

```
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   day        45211 non-null  int64
 9   month      45211 non-null  object
 10  duration   45211 non-null  int64
 11  campaign   45211 non-null  int64
 12  pdays      45211 non-null  int64
 13  previous   45211 non-null  int64
 14  y          45211 non-null  object
dtypes: float64(2), int64(5), object(8)
memory usage: 5.2+ MB
```

```
df.isna().sum()
```

```
age          9
job          0
marital      0
education    0
default      0
balance      3
housing      0
loan         0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
y            0
dtype: int64
```

```
for col in df.columns: #To Know unique values
    print(col,' ',df[col].nunique())
```

```
age   79
job   12
marital   3
education   4
default   2
balance   7168
housing   2
loan   2
day   31
month   12
duration   1573
campaign   48
pdays   559
previous   41
y   2
```

```
df.columns
```

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

```
for col in df.columns:
  print(col)
  print(df[col].nunique())
  print('-'*100)
```

```
age
79
----------------------------------------------------------------------
------------------------------
job
12
----------------------------------------------------------------------
------------------------------
marital
3
----------------------------------------------------------------------
------------------------------
education
4
----------------------------------------------------------------------
------------------------------
default
2
----------------------------------------------------------------------
------------------------------
balance
7168
----------------------------------------------------------------------
------------------------------
housing
2
----------------------------------------------------------------------
------------------------------
loan
2
----------------------------------------------------------------------
------------------------------
day
31
----------------------------------------------------------------------
------------------------------
```

```
month
12
----------------------------------------------------------------------
------------------------------
duration
1573
----------------------------------------------------------------------
------------------------------
campaign
48
----------------------------------------------------------------------
------------------------------
pdays
559
----------------------------------------------------------------------
------------------------------
previous
41
----------------------------------------------------------------------
------------------------------
y
2
----------------------------------------------------------------------
------------------------------
```

```python
for col in df.columns:
  print(col)
  print(df[col].unique())
  print('-'*100)
```

```
age
[999.  44.  33.  47.  35.  28.  nan  58.  43.  41.  29.  53.  57.  51.
  45.  60.  56.  32.  25.  40.  39.  52.  46.  36.  49.  59.  37.  50.
  54.  55.  48.  31.  42.  30.  27.  34.  38.  23.  26.  61.  22.  24.
  21.  20.  66.  62.  83.  75.  67.  70.  65.  68.  64.  69.  72.  71.
  19.  76.  85.  63.  90.  82.  73.  74.  78.  80.  94.  79.  77.  86.
  95.  81.  18.  89.  84.  87.  92.  93.  88.  -1.]
----------------------------------------------------------------------
------------------------------
job
['management' 'technician' 'entrepreneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed'
'housemaid'
 'student']
----------------------------------------------------------------------
------------------------------
marital
['married' 'single' 'divorced']
----------------------------------------------------------------------
------------------------------
```

```
education
['tertiary' 'secondary' 'unknown' 'primary']
------------------------------------------------------------------------
------------------------------
default
['no' 'yes']
------------------------------------------------------------------------
------------------------------
balance
[2.1430e+03 2.9000e+01 2.0000e+00 ... 8.2050e+03 1.4204e+04
1.6353e+04]
------------------------------------------------------------------------
------------------------------
housing
['yes' 'no']
------------------------------------------------------------------------
------------------------------
loan
['no' 'yes']
------------------------------------------------------------------------
------------------------------
day
[ 5  6  7  8  9 12 13 14 15 16 19 20 21 23 26 27 28 29 30  2  3  4 11
17
 18 24 25  1 10 22 31]
------------------------------------------------------------------------
------------------------------
month
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar' 'apr'
'sep']
------------------------------------------------------------------------
------------------------------
duration
[ 261  151   76 ... 1298 1246 1556]
------------------------------------------------------------------------
------------------------------
campaign
[ 1  2  3  5  4  6  7  8  9 10 11 12 13 19 14 24 16 32 18 22 15 17 25
21
 43 51 63 41 26 28 55 50 38 23 20 29 31 37 30 46 27 58 33 35 34 36 39
44]
------------------------------------------------------------------------
------------------------------
pdays
[ -1 151 166  91  86 143 147  89 140 176 101 174 170 167 195 165 129
188
 196 172 118 119 104 171 117 164 132 131 123 159 186 111 115 116 173
178
 110 152  96 103 150 175 193 181 185 154 145 138 126 180 109 158 168
```

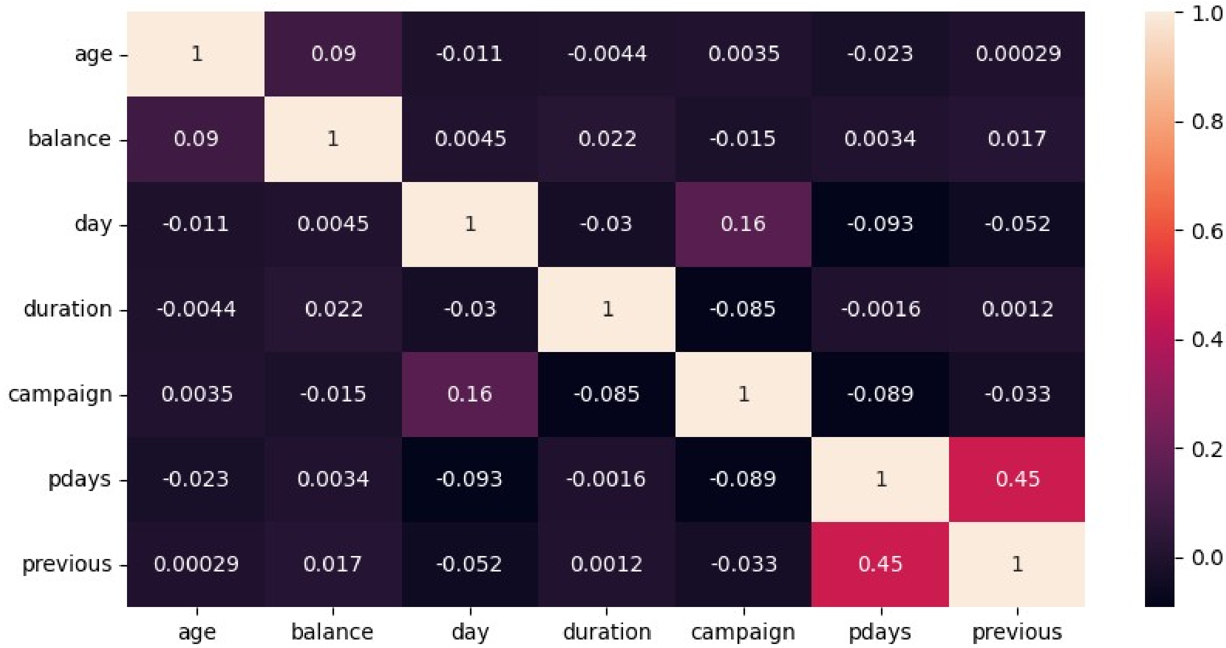
```
97
 182 127 130 194 125 105 102  26 179  28 183 155 112 120 137 124 187
190
 113 162 134 169 189   8 144 191 184 177   5  99 133  93  92  10 100
156
 198 106 153 146 128   7 121 160 107  90  27 197 136 139 122 157 149
135
  30 114  98 192 163  34  95 141  31 199  94 108  29 268 247 253 226
244
 239 245 204 231 238 258 230 254 265  71 223 246 250 266 240 205 261
259
 241 260 234 251 225 161 237 262 248 255 220 227 206 224 249 235 228
263
   2 270 232 252 207 200 269 233 256 273 272 242 264 208 214 222 271
203
 221 202 216 201 257 229 210 217  75 213  73  76 267 211 215  77 236
82
   6 209 274   1 243 212 275  80 276   9 279  12 280  88 277  85  84
219
  24  21 282  41 294  49 329 307 303 331 308 300  64 314 287 330 332
302
 323 318 333  60 326 335 313 312 305 325 327 336 309 328 322  39 316
292
 295 310 306 320 317 289  57 321 142 339 301 315 337 334 340 319  17
74
 148 341 299 344 342 324 345 346 304 281 343 338  14 347  15 291 348
349
 285 350 284  25 283 278  81   4  87  83  79  70  13 293  37  78  63
22
 296 355  66  19  35 360 357 354 351 362 358 365 298 286 364 363  47
361
 288 366 356 352 359 297 367 353 368  42 290  67 371 370 369  50  36
373
 374 372 311 375 378  59 379  40  18  43  20  69  38 385  56  55  44
391
  72 390  32  62 399 393  65 377 395 388 389 386  61 412 405 434 394
382
 459 440 397 383  68 461 462 463 422  51 457 430 442 403 454 428 392
410
 401 474 475 477 478  54 476 380 479  45  46 495  58  48 518  52 515
520
 511 536 387 218  33 544 435 436 555 433 446 558 469 616 561 553 384
592
 467 585 480 421 667 626 426 595 381 376 648 521 452 449 633 398  53
460
 670 551 414 557 687 404 651 686 425 504 578 674 416 586 411 756 450
745
 514 417 424 776 396 683 529 439 415 456 407 458 532 481 791 701 531
792
```

```
 413 445 535 784 419 455 491 431 542 470 472 717 437   3 782 728 828
524
 562 761 492 775 579 493 464 760 466 465 656 831 490 432 655 427 749
838
 769 587 778 854 779 850 771 594 842 589 603 484 489 486 409 444 680
808
 485 503 690 772 774 526 420 528 500 826 804 508 547 805 541 543 871
550
 530]
----------------------------------------------------------------------
------------------------------
previous
[  0   3   1   4   2  11  16   6   5  10  12   7  18   9  21   8  14
15
  26  37  13  25  20  27  17  23  38  29  24  51 275  22  19  30  58
28
  32  40  55  35  41]
----------------------------------------------------------------------
------------------------------
y
['no' 'yes']
----------------------------------------------------------------------
------------------------------
```

FEATURE SELECTION

```
df.corr()

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-1-2f6f6606aa2c> in <cell line: 1>()
----> 1 df.corr()

NameError: name 'df' is not defined
```

```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True)

<ipython-input-15-fe2252758f39>:2: 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(),annot=True)

<Axes: >
```



CHI SQUARE & ANNOVA TEST

```
df_copy=df.copy()
#Label encoding before feature selection
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for col in df_copy.columns:
  df_copy[col]=le.fit_transform(df_copy[col])
df_copy
```

```
       age  job  marital  education  default  balance  housing  loan  
day  \
0       78    4        1          2        0     3036        1     0  
4
1       27    9        2          1        0      945        1     0  
4
2       16    2        1          1        0      918        1     1  
4
3       30    1        1          3        0     2420        1     0  
4
4       16   11        2          3        0      917        0     0  
4
...    ...  ...      ...        ...      ...      ...      ...   ...  
...
45206   34    9        1          2        0     1741        0     0  
16
45207   54    5        0          0        0     2639        0     0  
16
```

```
45208   55    5         1          1        0     5455        0     0
16
45209   40    1         1          1        0     1584        0     0
16
45210   20    2         1          1        0     3779        0     0
16

       month  duration  campaign  pdays  previous  y
0          8       261         0      0         0  0
1          8       151         0      0         0  0
2          8        76         0      0         0  0
3          8        92         0      0         0  0
4          8       198         0      0         0  0
...      ...       ...       ...    ...       ... ..
45206      9       975         2      0         0  1
45207      9       456         1      0         0  1
45208      9      1116         4    181         3  1
45209      9       508         3      0         0  0
45210      9       361         1    185        11  0

[45211 rows x 15 columns]
```

```
x_discrete=df_copy[['job', 'marital', 'education', 'default',
'housing', 'loan', 'month']]
x_continuous=df_copy[['age' ,    'balance'  ,'day'     ,'duration' ,
     'campaign' ,     'pdays' ,  'previous']]
y_copy=df_copy.iloc[:,-1]

#Chi Square Test for feature selection in case of discrete input
labels
from sklearn.feature_selection import chi2
score1=chi2(x_discrete,y_copy)
score1
```

```
(array([182.45226044,  29.76606652,  90.61772256,  22.31387496,
        388.94971474, 176.51613693,  44.32190507]),
 array([1.41257633e-41, 4.87449759e-08, 1.74292216e-21, 2.31527677e-
06,
        1.40128480e-86, 2.79337524e-40, 2.78581489e-11]))
```

```
f_value1=pd.Series(score1[0],index=x_discrete.columns)
f_value1.sort_values(ascending=False)
```

```
housing      388.949715
job          182.452260
loan         176.516137
education     90.617723
month         44.321905
marital       29.766067
default       22.313875
dtype: float64
```

```
p_value1=pd.Series(score1[1],index=x_discrete.columns)
p_value1.sort_values(ascending=False)
```

```
default      2.315277e-06
marital      4.874498e-08
month        2.785815e-11
education    1.742922e-21
loan         2.793375e-40
job          1.412576e-41
housing      1.401285e-86
dtype: float64
```

```
#Annova Test for feature selection in case of continuous input labels
from sklearn.feature_selection import f_classif
score2=f_classif(x_continuous,y_copy)
score2
```

```
(array([  26.58010222,  311.62865296,   36.35900965, 9021.94787625,
         245.7274607 ,  470.12762293,  599.58462133]),
 array([2.53897219e-007, 1.65228194e-069, 1.65388016e-009,
0.00000000e+000,
        3.10161380e-055, 1.01716123e-103, 1.48875810e-131]))
```

```
f_value2=pd.Series(score2[0],index=x_continuous.columns)
f_value2.sort_values(ascending=False)
```

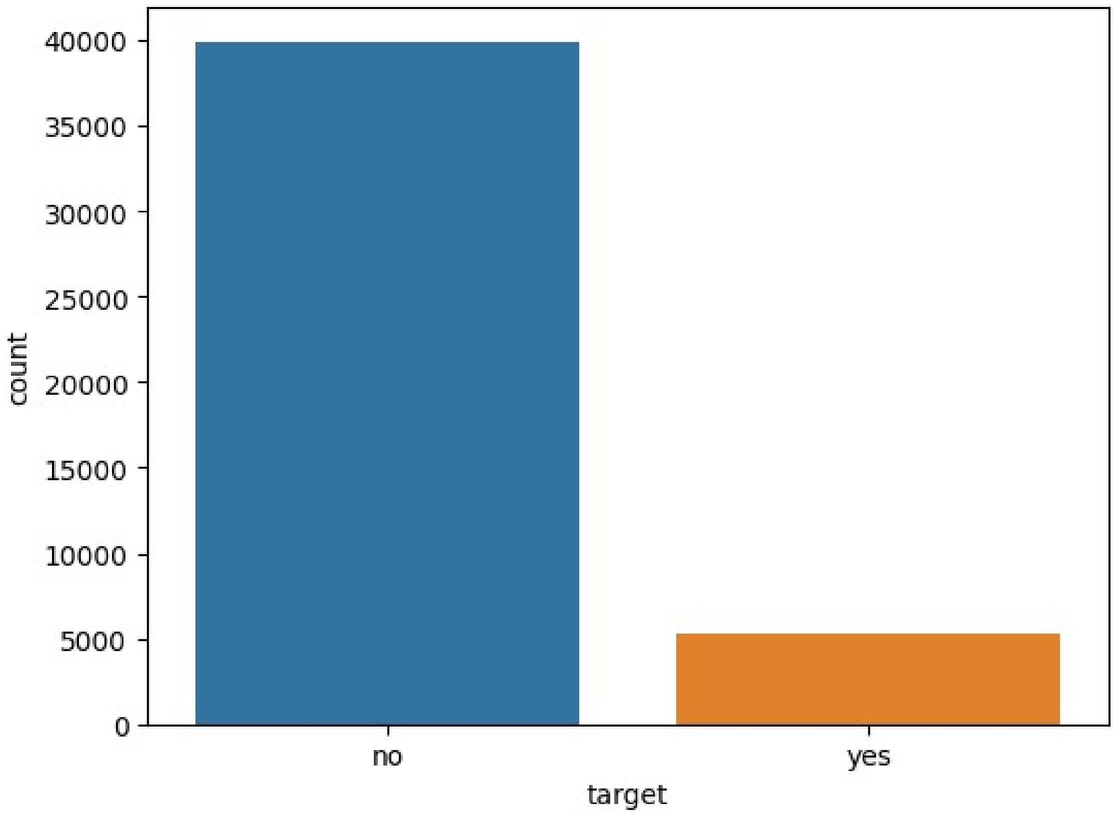
```
duration    9021.947876
previous     599.584621
pdays        470.127623
balance      311.628653
campaign     245.727461
day           36.359010
age           26.580102
dtype: float64
```

```
p_value2=pd.Series(score2[1],index=x_continuous.columns)
p_value2.sort_values(ascending=False)
```

```
age          2.538972e-07
day          1.653880e-09
campaign     3.101614e-55
balance      1.652282e-69
pdays       1.017161e-103
previous    1.488758e-131
duration     0.000000e+00
dtype: float64
```

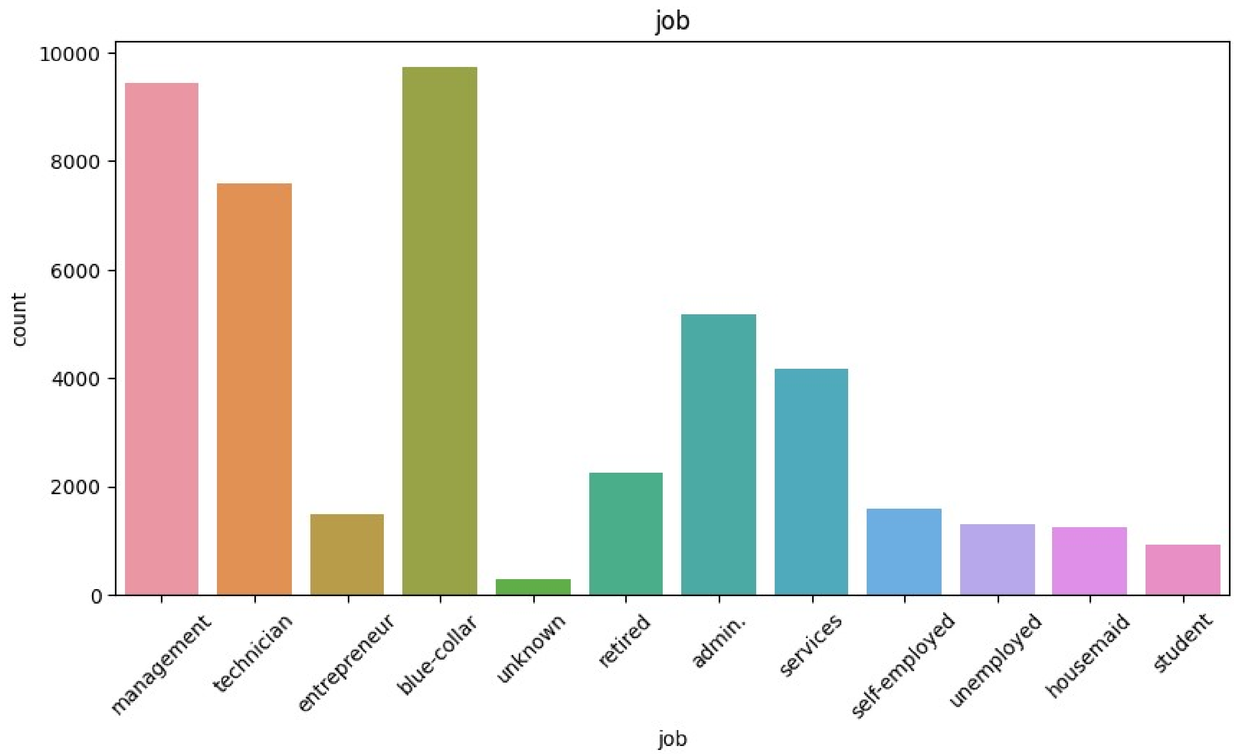
VISUALIZATION

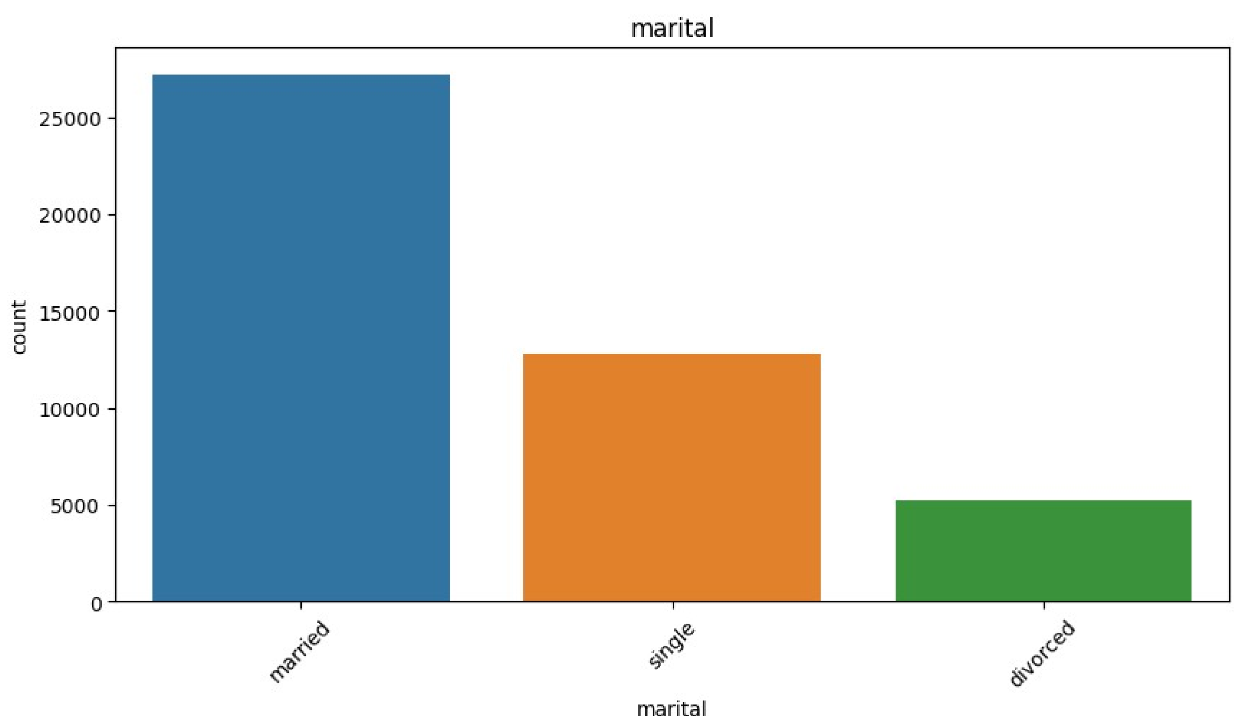
```
sns.countplot(x=df['y'])
plt.xlabel('target')

df['y'].value_counts()

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

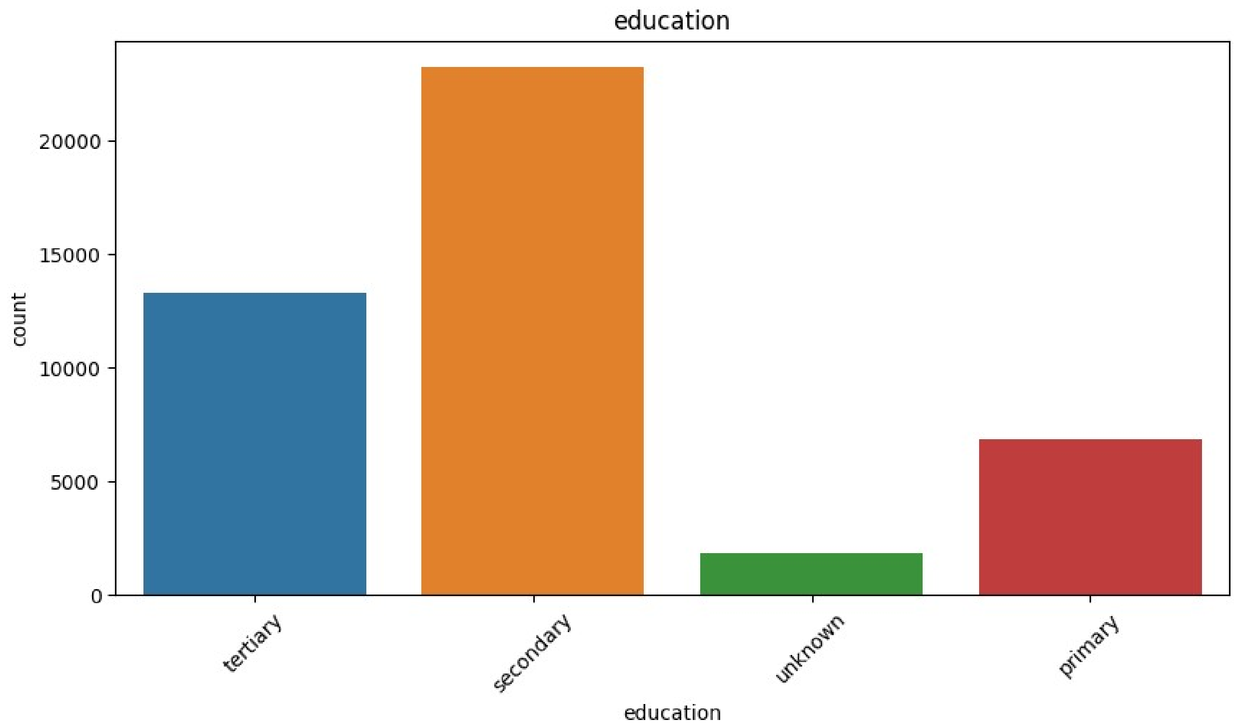


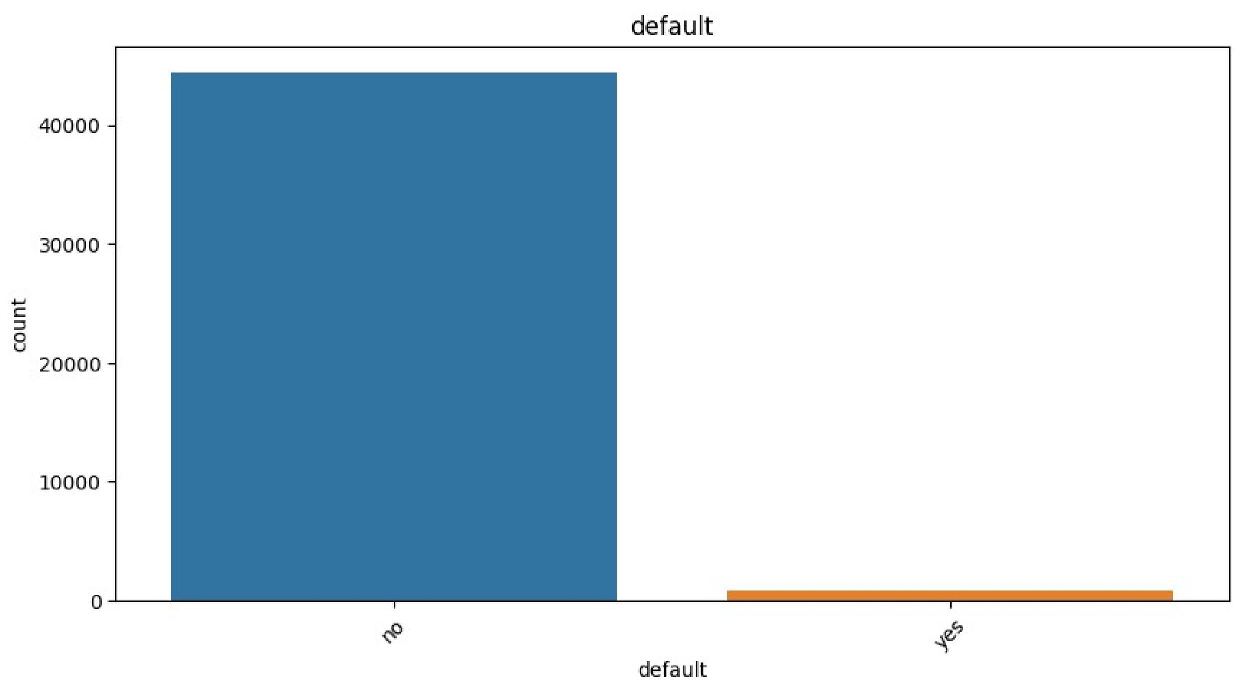
Based on this analysis, we can conclude that the dataset is imbalanced.

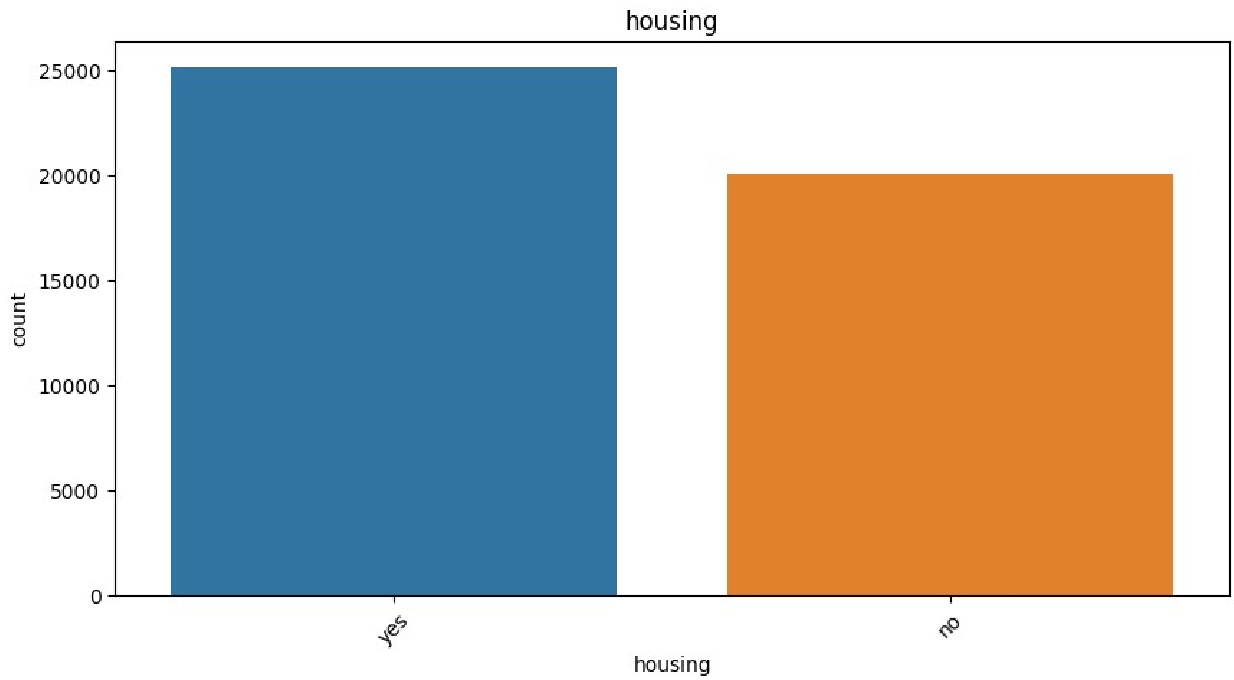
```
#univariate analysis
import seaborn as sns
categorical_cols= [col for col in df.columns if df[col].dtype ==
'object']
for i in categorical_cols:
  plt.figure(figsize=(10,5))
  sns.countplot(x=i,data=df)
  plt.title(i)
  plt.xticks(rotation=45)
```

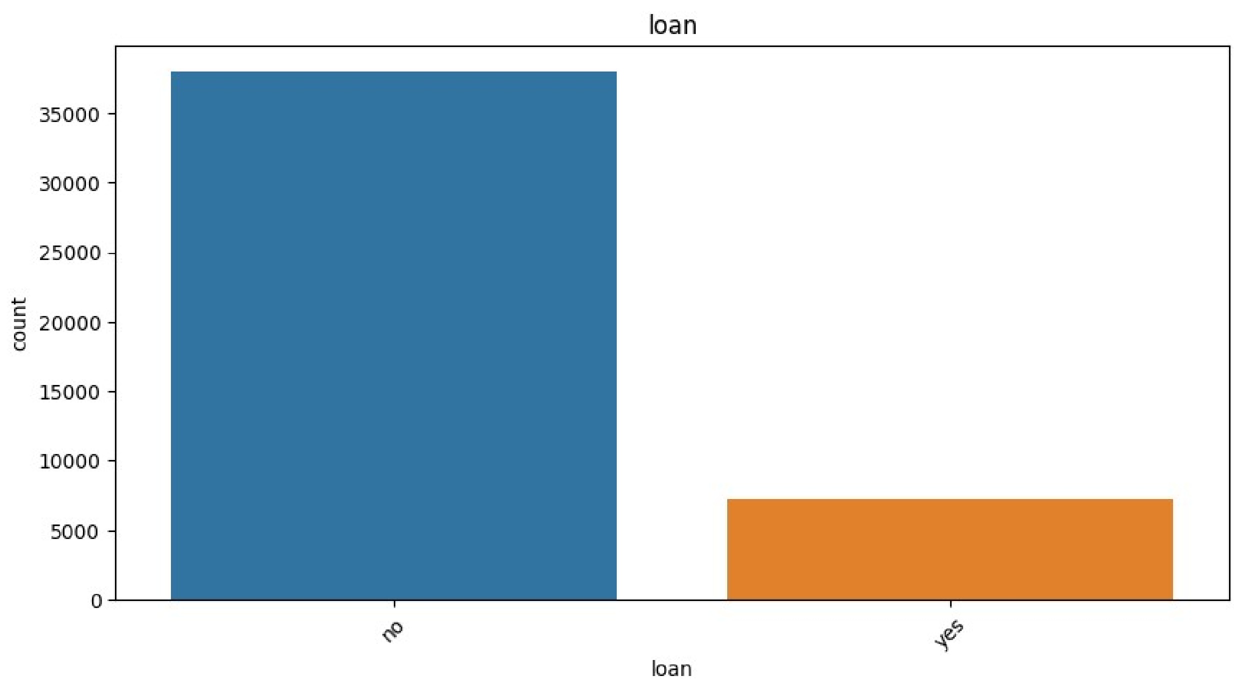

job
count
10000
8000
6000
4000
2000
0
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student
job

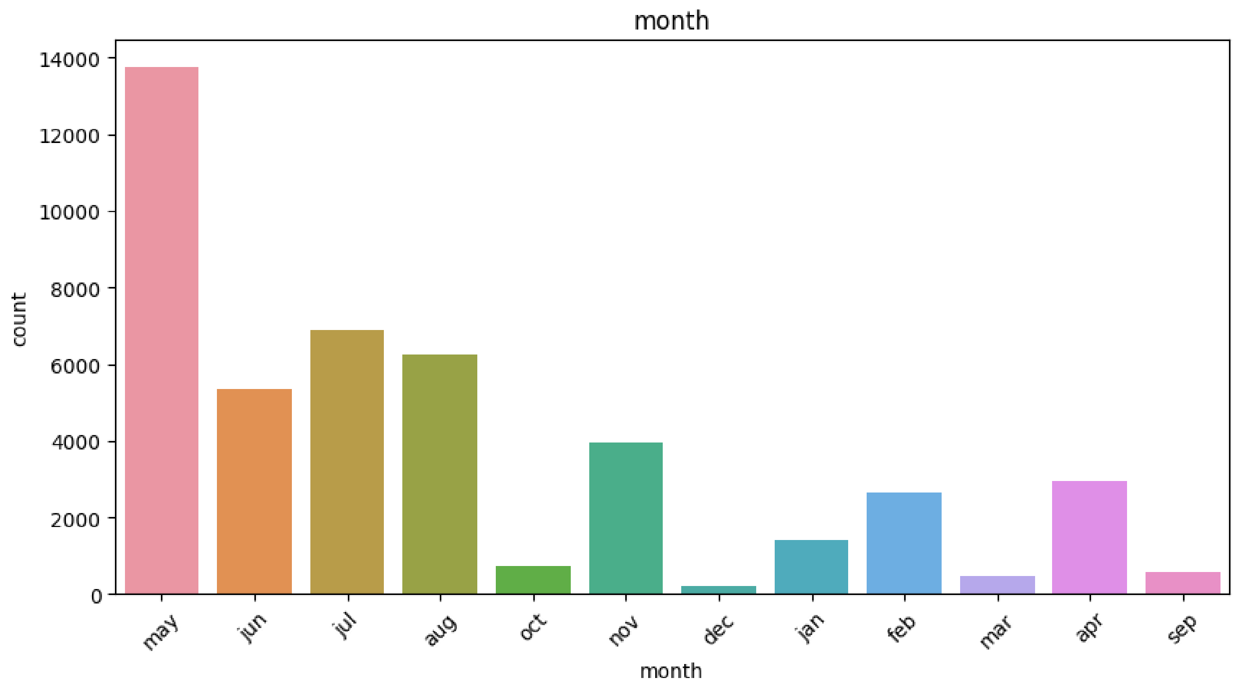

marital
count
25000
20000
15000
10000
5000
0
married
single
divorced
marital

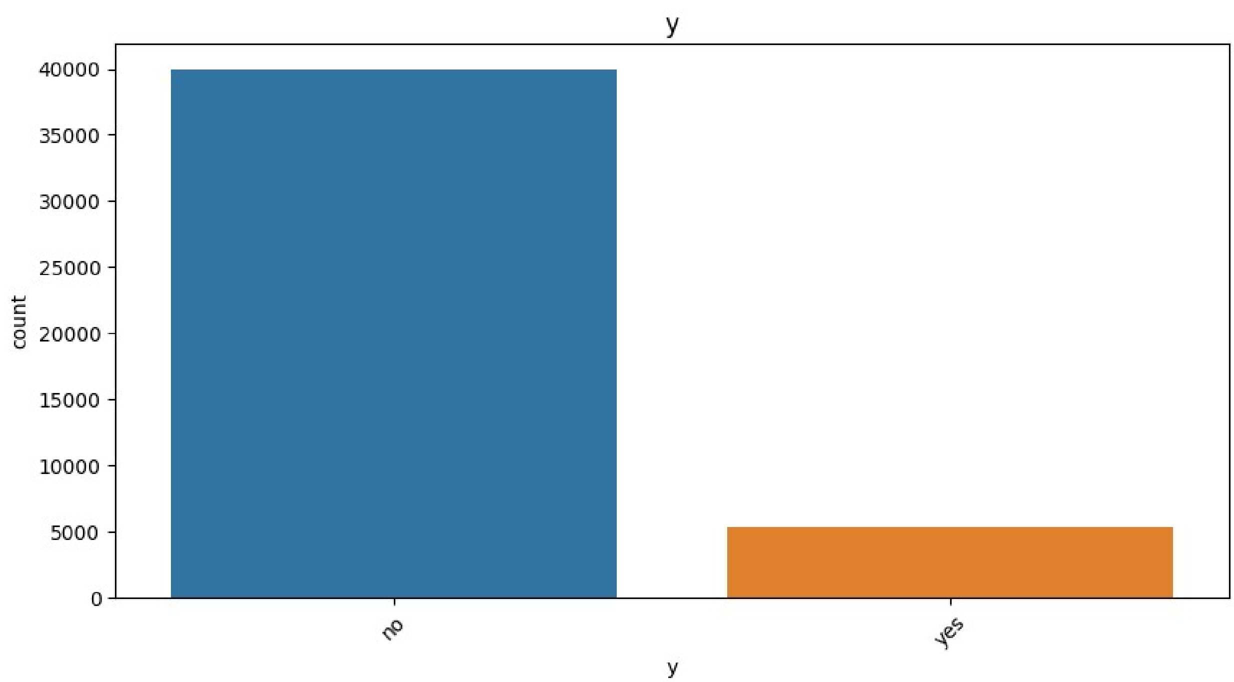

education
20000
15000
10000
5000
0
count
tertiary
secondary
unknown
primary
education


default
40000
30000
20000
10000
0
count
no
yes
default

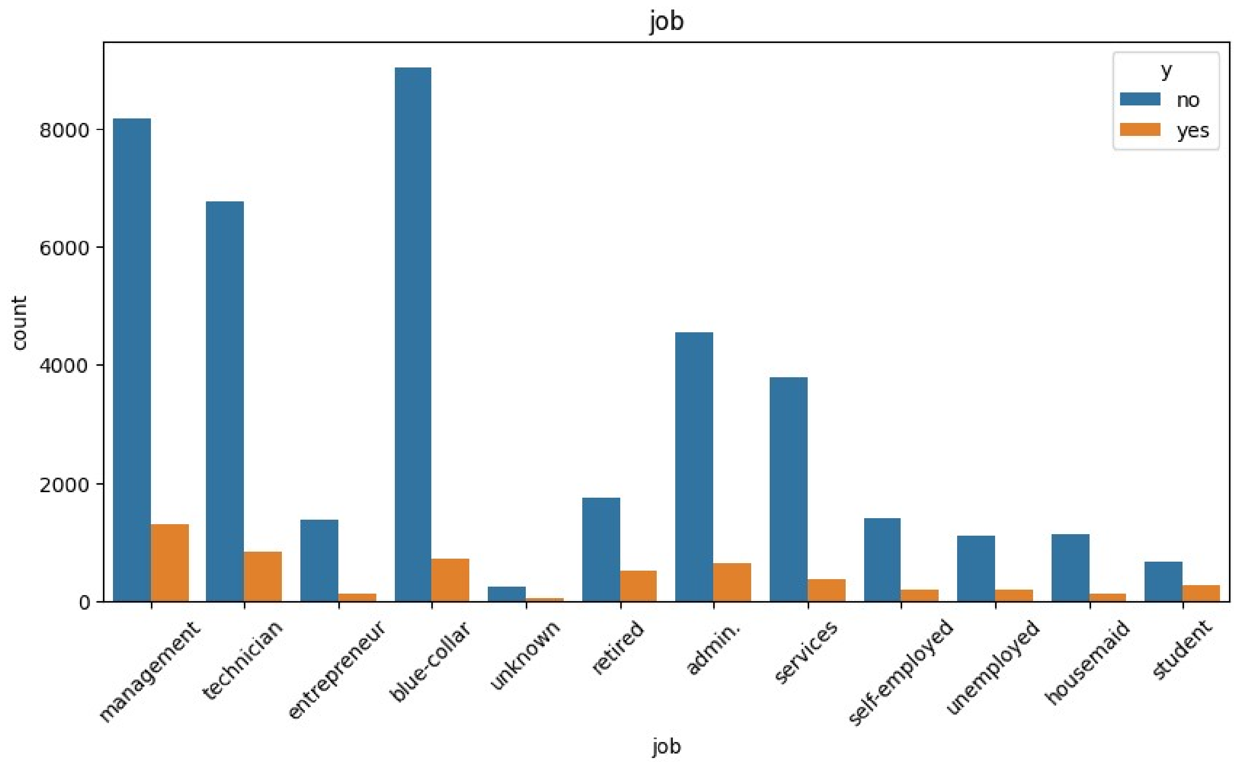

housing
25000
20000
15000
10000
5000
0
count
yes
no
housing

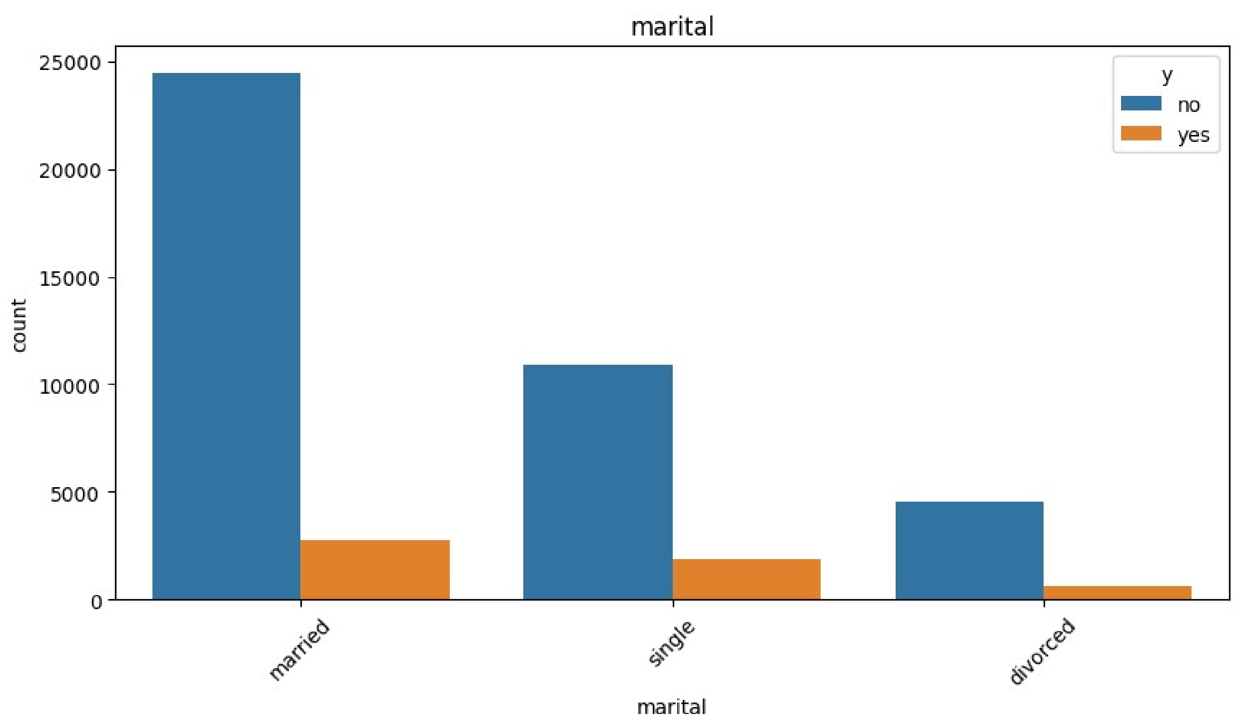

loan
35000
30000
25000
20000
15000
10000
5000
0
count
no
yes
loan

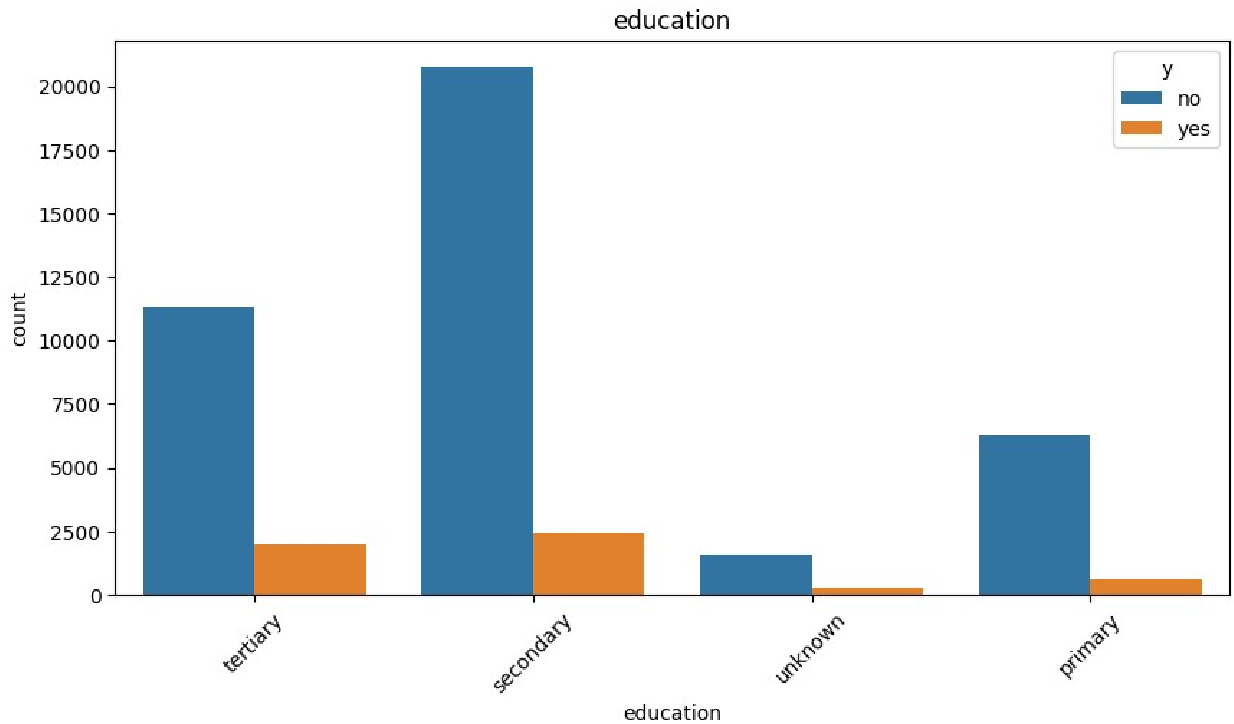


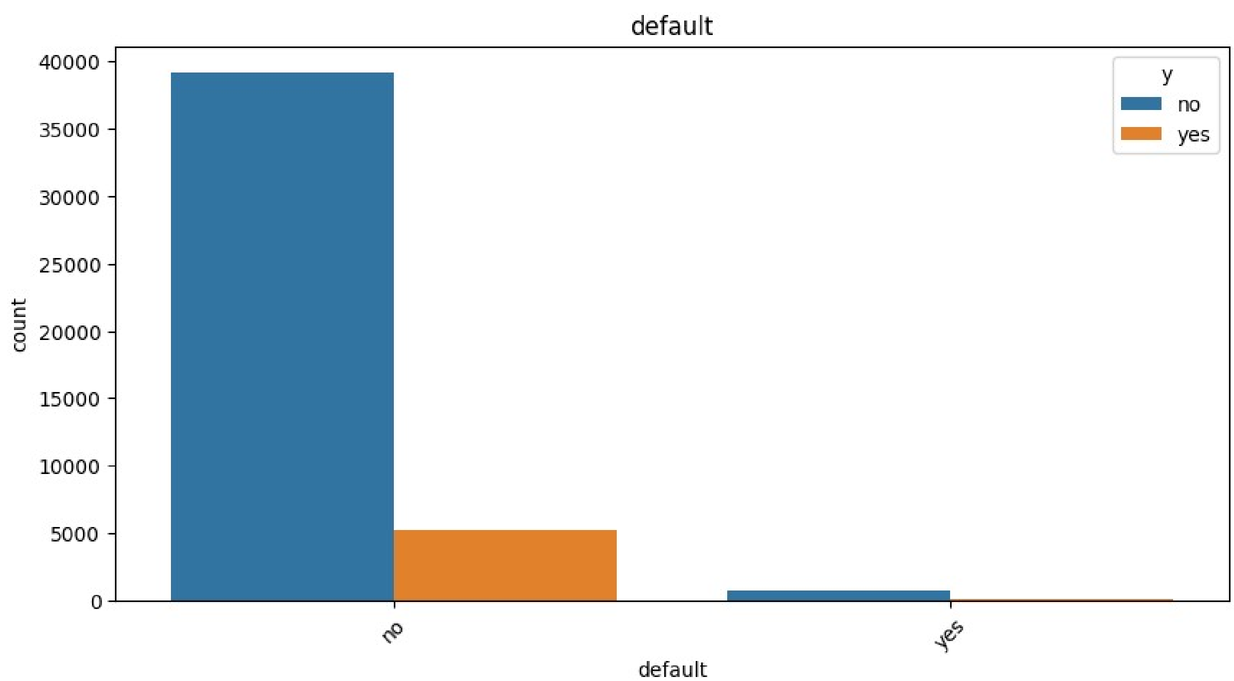


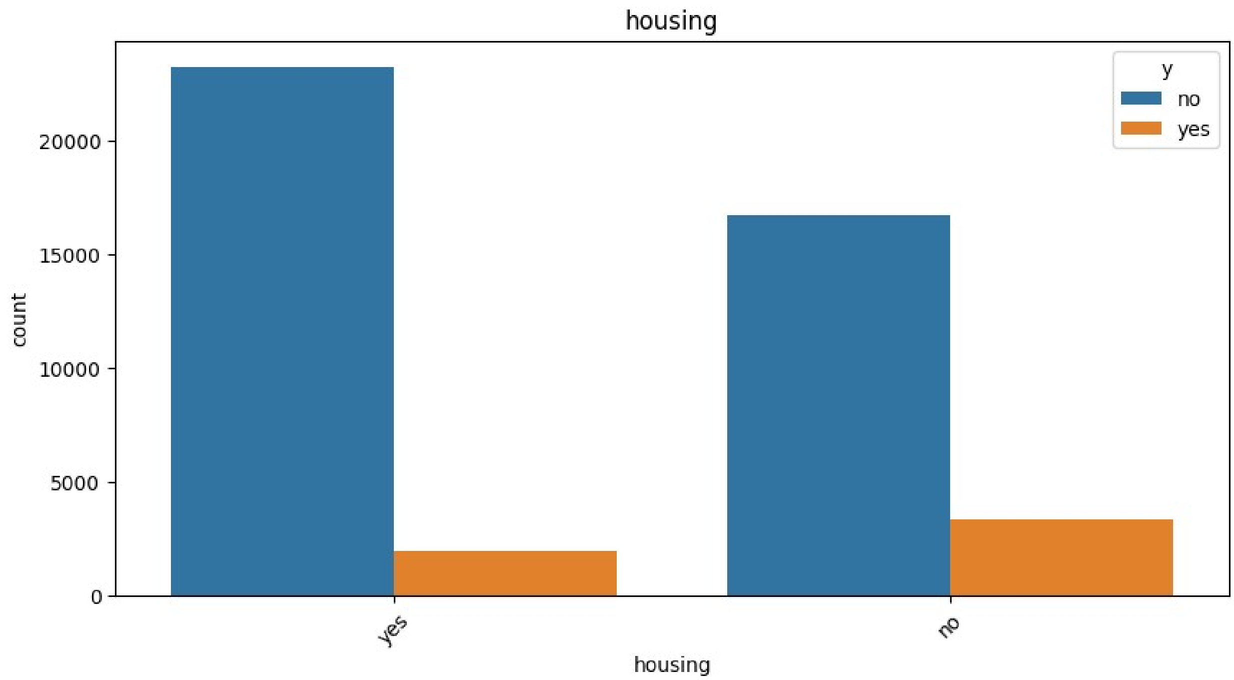

```
#bivariate analysis
for i in categorical_cols:
  plt.figure(figsize=(10,5))
  sns.countplot(x=df[i],hue=df['y'])
  plt.title(i)
  plt.xticks(rotation=45)
```

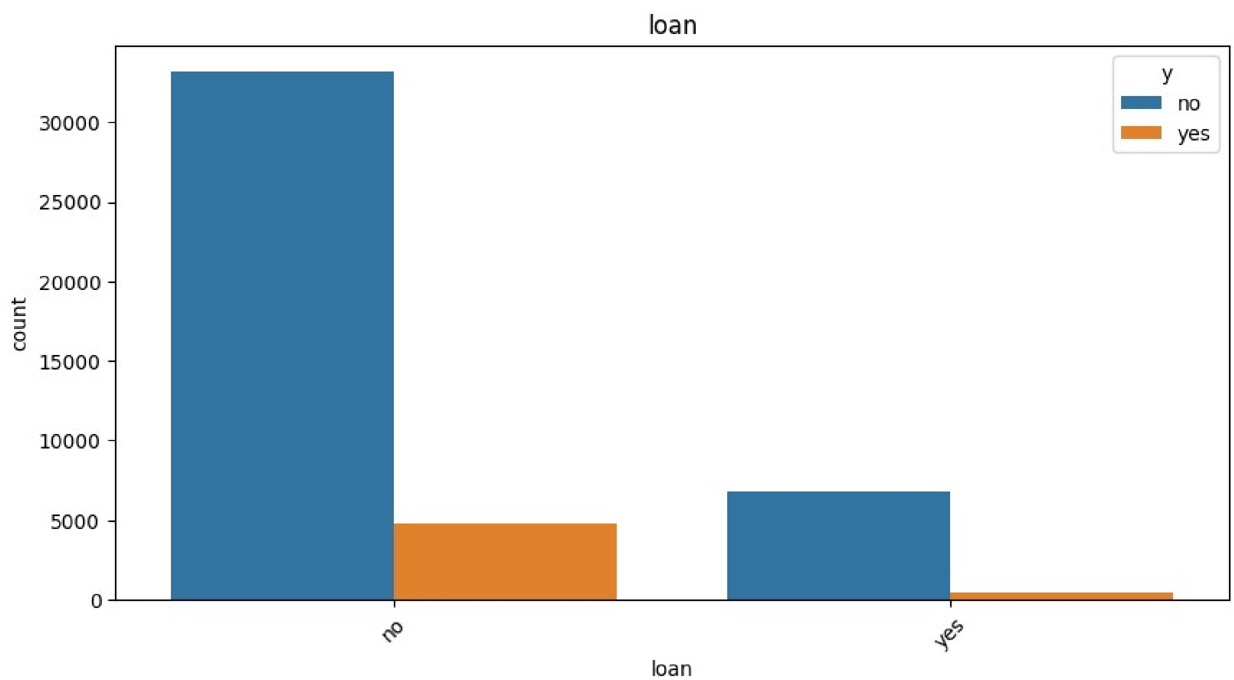

job
y
no
yes
count
8000
6000
4000
2000
0
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student
job

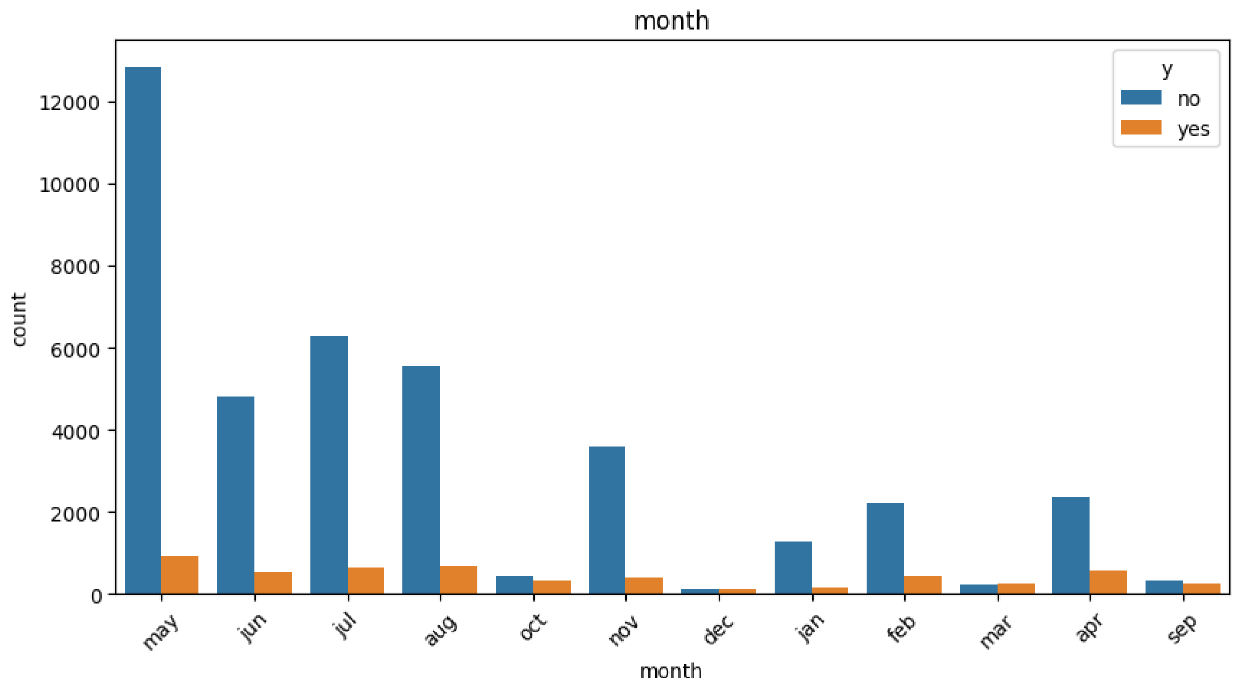

marital
y
no
yes
count
25000
20000
15000
10000
5000
0
married
single
divorced
marital

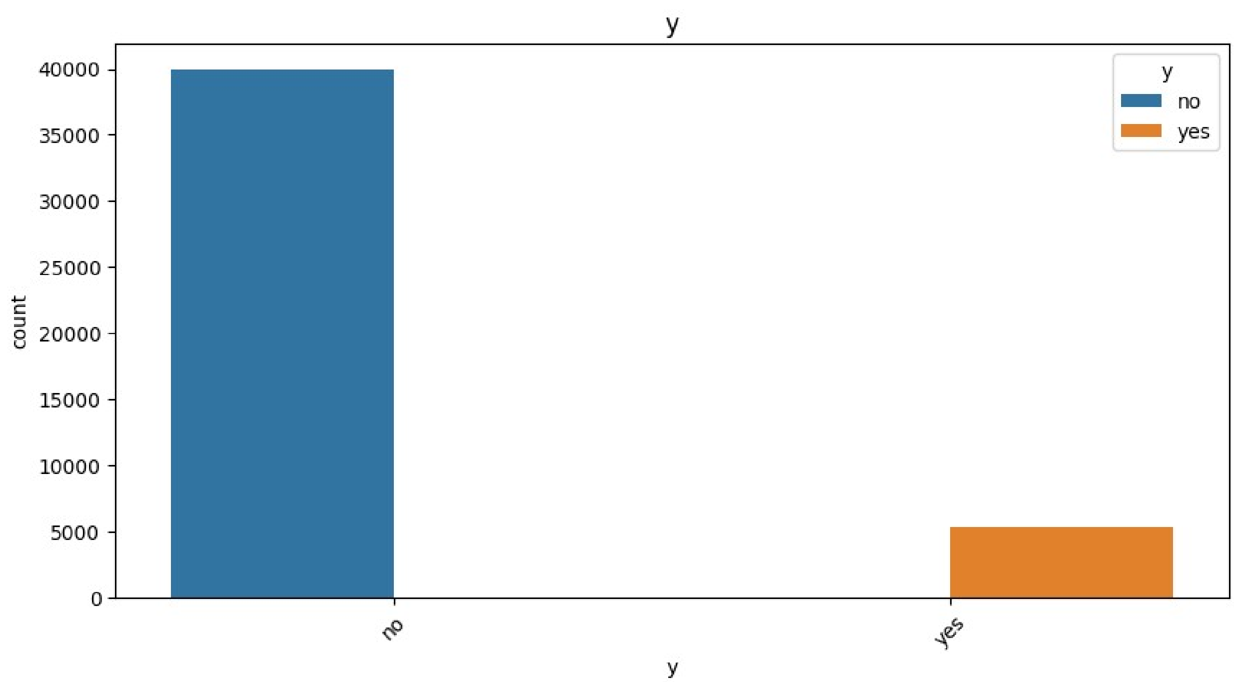

education
y
no
yes
20000
17500
15000
12500
10000
7500
5000
2500
0
count
tertiary
secondary
unknown
primary
education


default
y
no
yes
40000
35000
30000
25000
20000
15000
10000
5000
0
count
no
yes
default


housing
y
no
yes
count
0
5000
10000
15000
20000
yes
no
housing


loan
y
no
yes
count
0
5000
10000
15000
20000
25000
30000
no
yes
loan






```
import pandas as pd
contingency_table = pd.crosstab(df['marital'], df['housing'],
margins=True, margins_name="Total")
contingency_table
```

```
housing      no    yes  Total
marital
```

```
divorced   2300   2907   5207
married   11893  15321  27214
single     5888   6902  12790
Total     20081  25130  45211
```

HANDLING MISSING VALUES

```
df.isna().sum()
```

```
age          9
job          0
marital      0
education    0
default      0
balance      3
housing      0
loan         0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
y            0
dtype: int64
```

```
df['age'] = df['age'].fillna(df['age'].median())     # Filing the null values with median
df['balance'] = df['balance'].fillna(df['balance'].median()) # Filing the null values with median
```

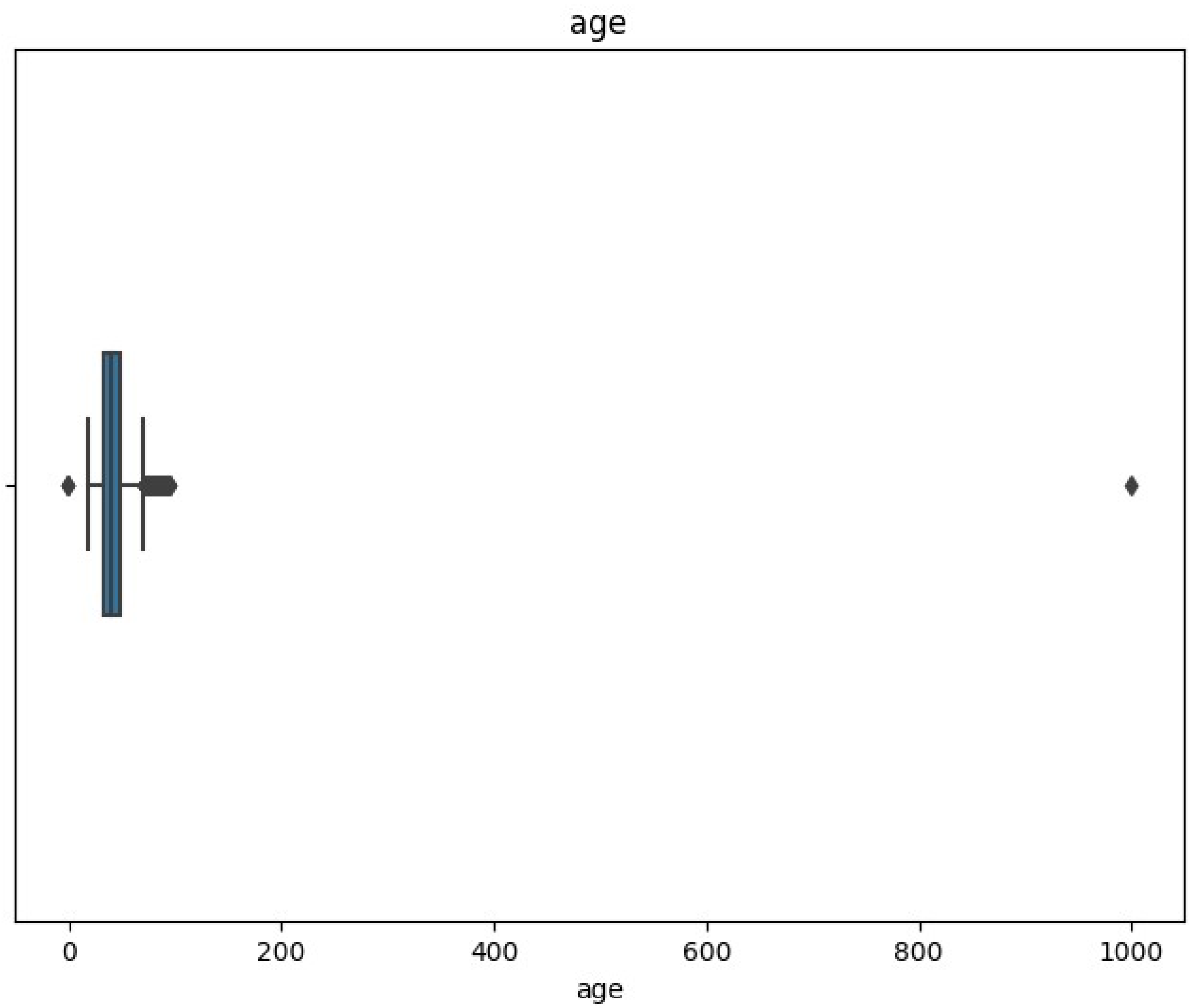
In some columns,missing values has been represented as unknown

```
for i in categorical_cols:
  mode=df[i].mode()[0]
  df[i]=df[i].replace('unknown',mode)
```

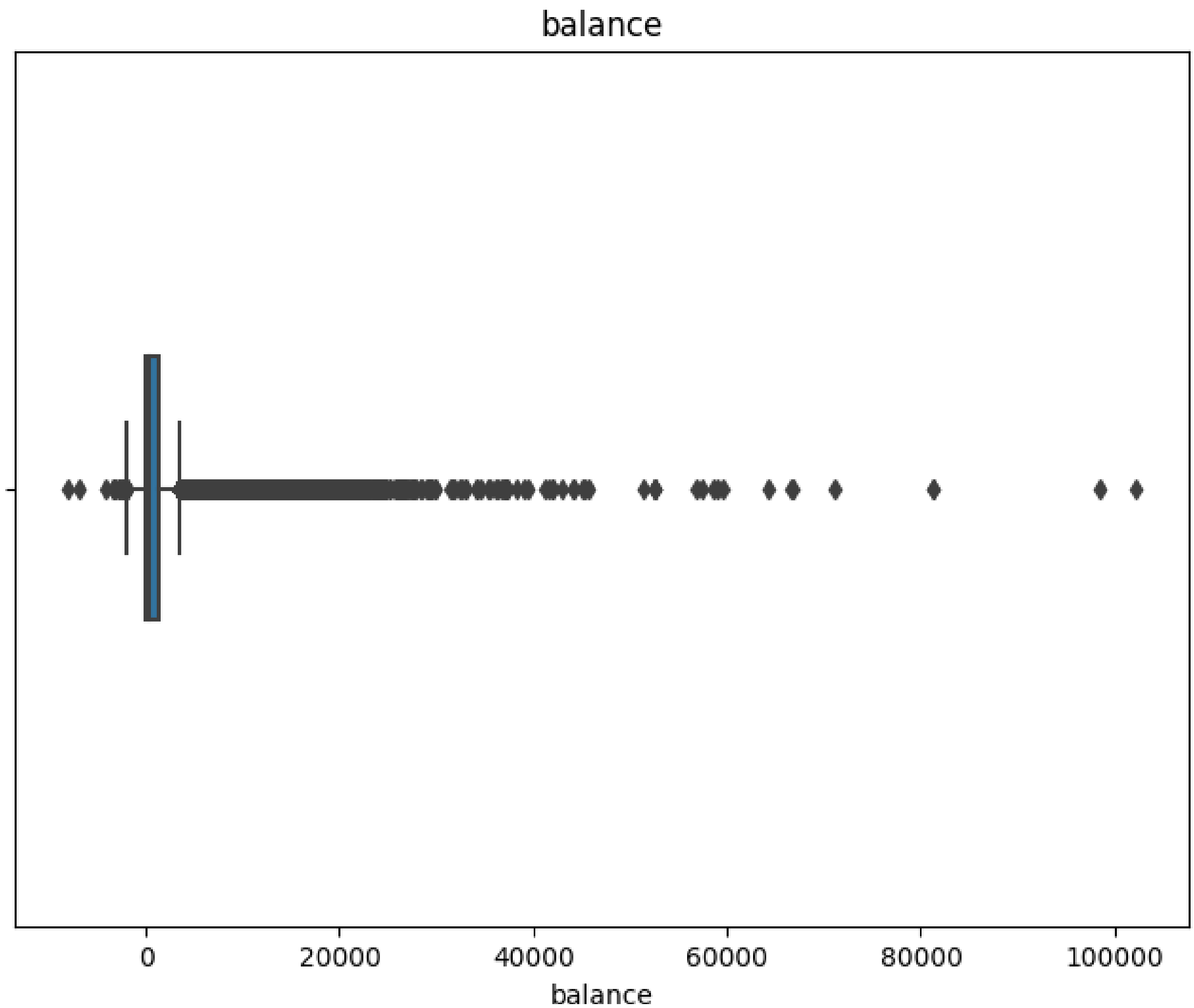
DEALING WITH OUTLIERS

```

numerical_cols=['age','balance','day','duration', 'campaign', 'pdays','previous']
for i in numerical_cols:
    plt.figure(figsize=(8, 6))
    sns.boxplot(x=i , data=df, orient='v', width=0.3)
```

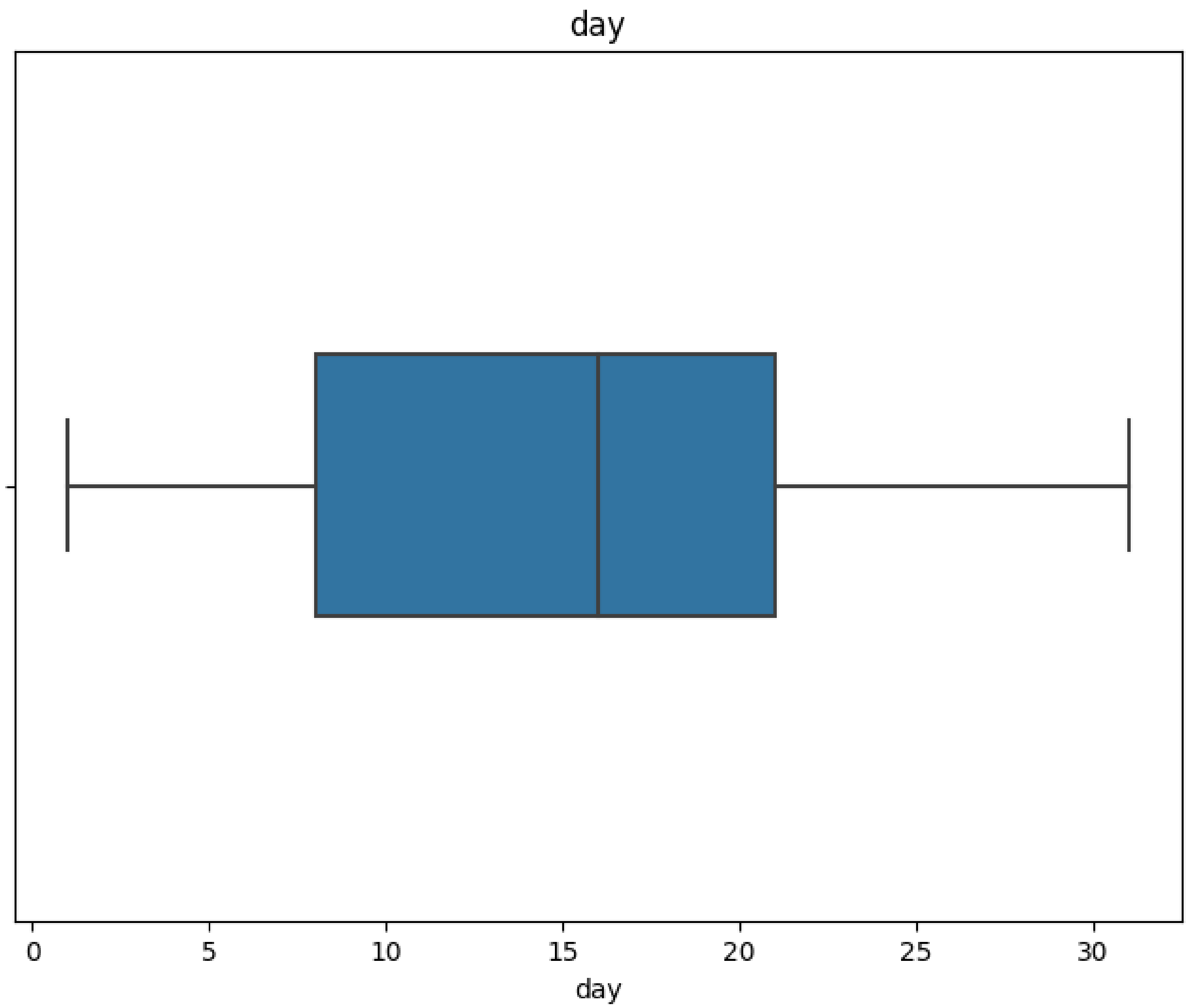
```
    plt.title(i)
    plt.show()

/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```



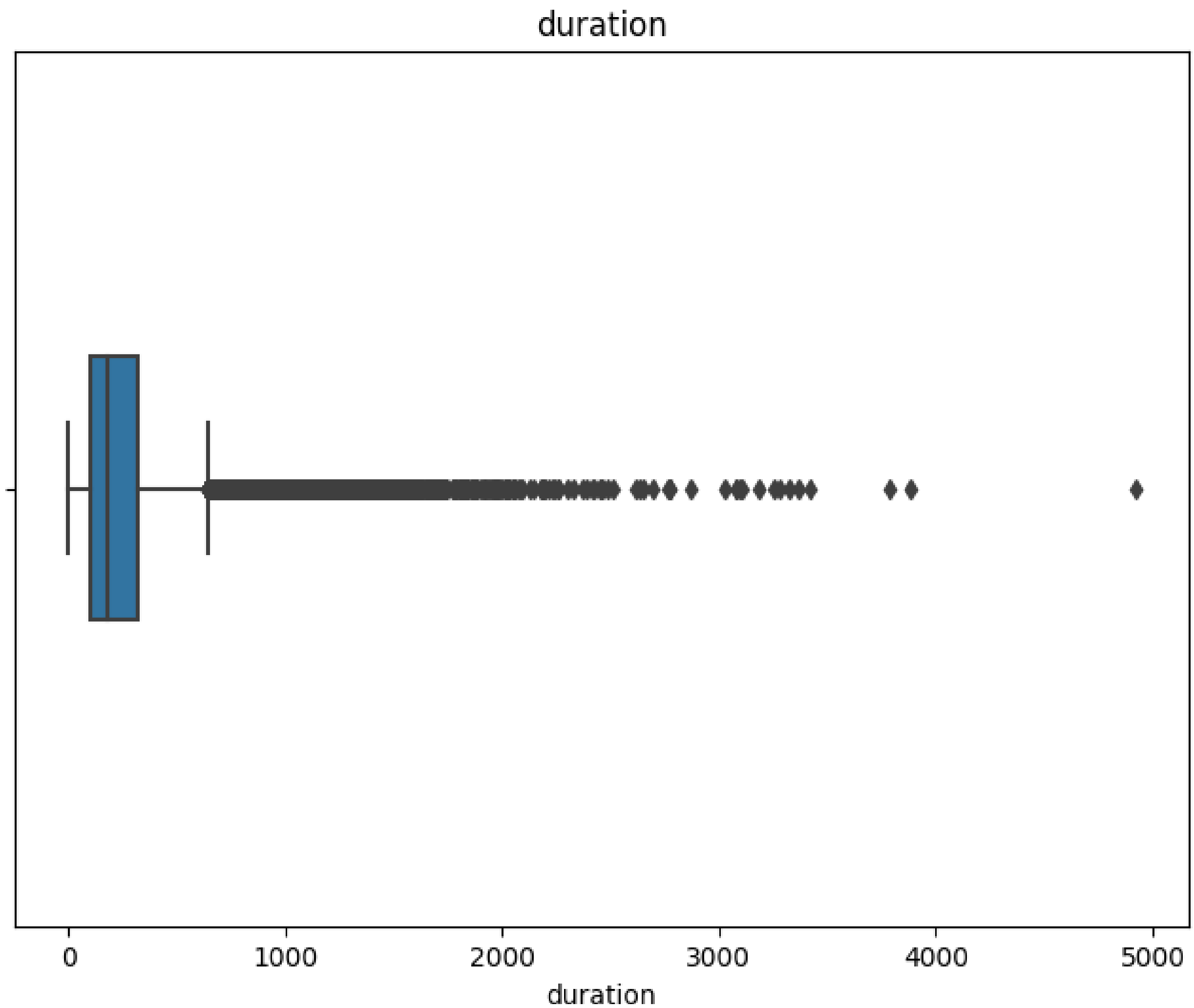

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```



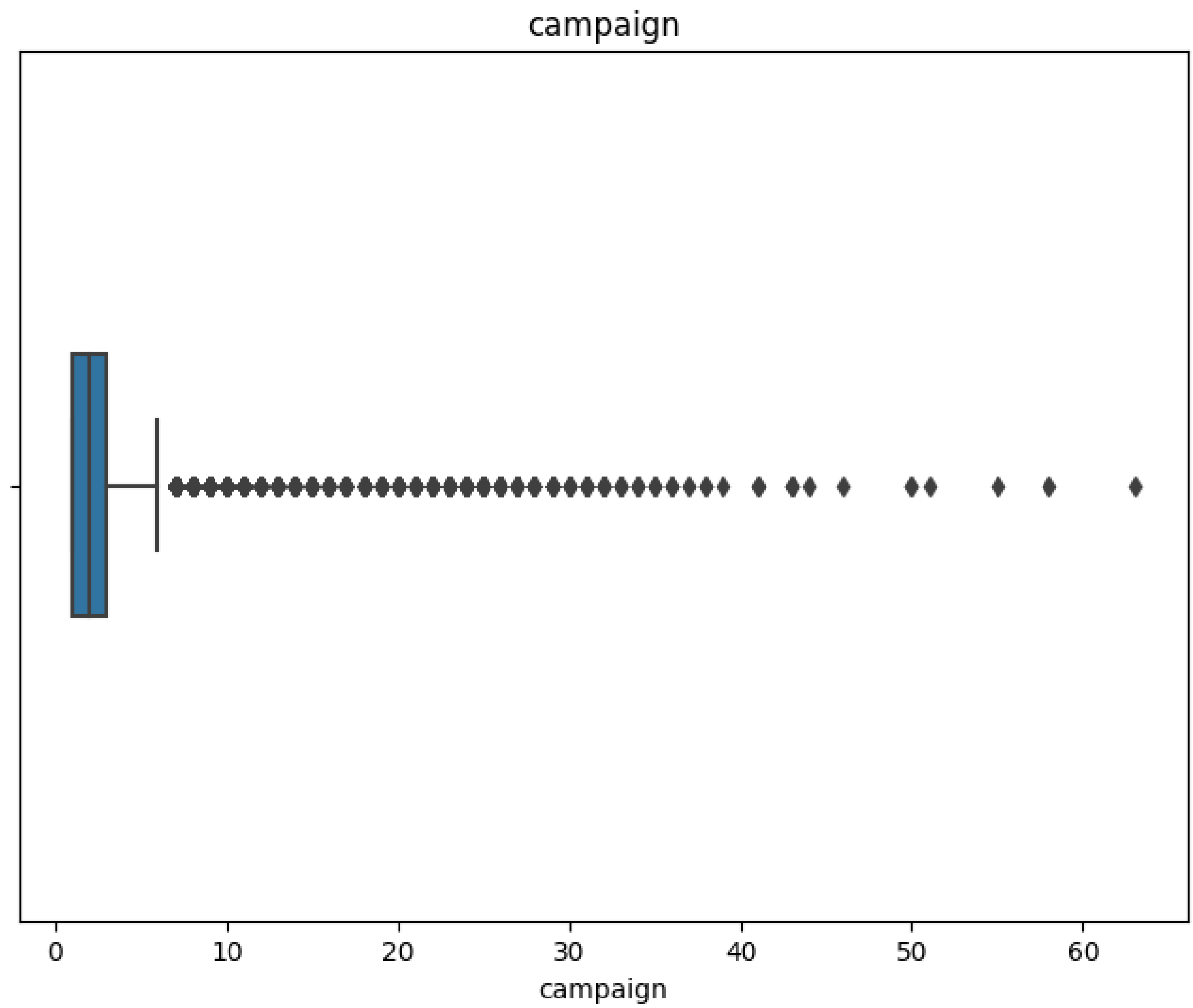

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```



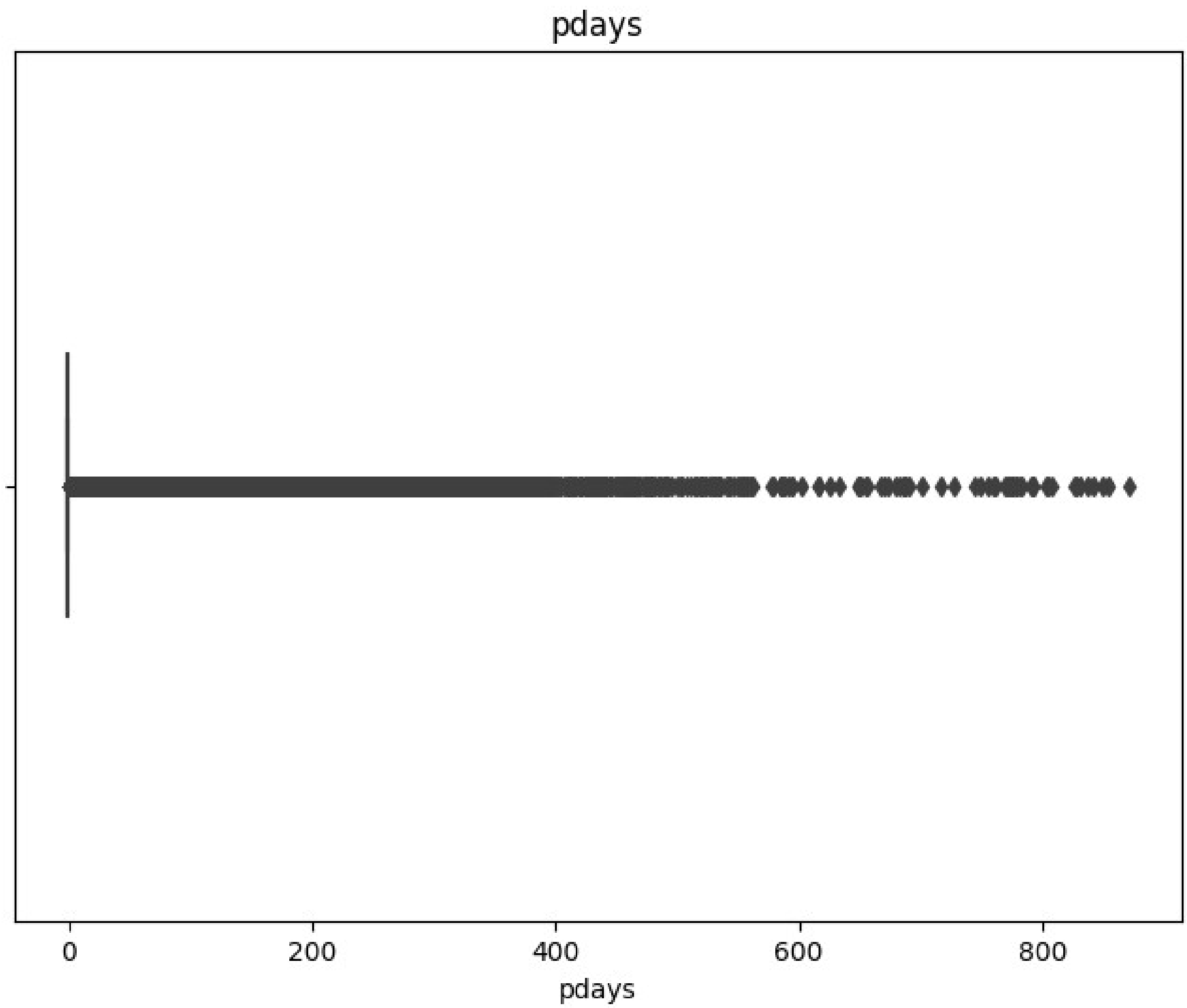

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```



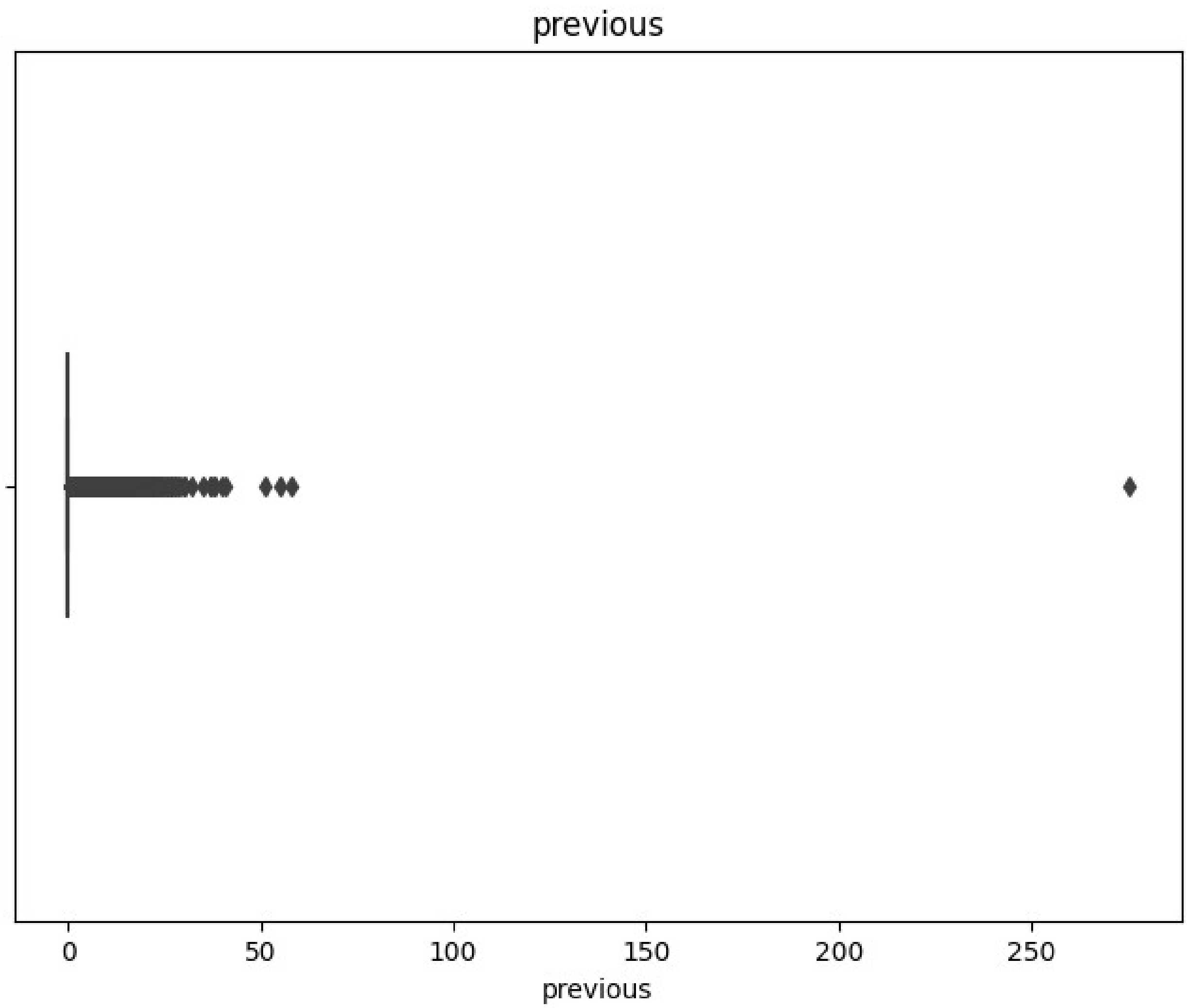

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```




```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```




```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1599:
UserWarning: Vertical orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```




```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
threshold = 1.5
df= df[~((df < (Q1 - threshold * IQR)) | (df > (Q3 + threshold *
IQR))).any(axis=1)]
```

```
<ipython-input-32-6865bb37bd72>:1: FutureWarning: The default value of
numeric_only in DataFrame.quantile 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.
  Q1 = df.quantile(0.25)
<ipython-input-32-6865bb37bd72>:2: FutureWarning: The default value of
numeric_only in DataFrame.quantile 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.
  Q3 = df.quantile(0.75)
<ipython-input-32-6865bb37bd72>:5: FutureWarning: Automatic reindexing
```

```
on DataFrame vs Series comparisons is deprecated and will raise
ValueError in a future version. Do `left, right = left.align(right,
axis=1, copy=False)` before e.g. `left == right`
  df= df[~((df < (Q1 - threshold * IQR)) | (df > (Q3 + threshold *
IQR))).any(axis=1)]
```

ENCODING USING GET_DUMMIES

```
df1=pd.get_dummies(df[['job', 'marital', 'education', 'default',
'housing', 'loan']],drop_first=True)
df1
```

```
       job_blue-collar  job_entrepreneur  job_housemaid
job_management  \
1                    0                 0              0
0
2                    0                 1              0
0
3                    1                 0              0
0
4                    1                 0              0
0
5                    0                 0              0
1
...                ...               ...            ...              ..
.
45196                0                 0              0
0
45197                0                 0              0
1
45198                0                 0              0
1
45202                0                 0              0
0
45209                1                 0              0
0

       job_retired  job_self-employed  job_services  job_student  \
1                0                  0             0            0
2                0                  0             0            0
3                0                  0             0            0
4                0                  0             0            0
5                0                  0             0            0
...            ...                ...           ...          ...
45196            0                  0             0            1
45197            0                  0             0            0
45198            0                  0             0            0
45202            0                  0             0            0
```

```
45209          0                   0              0            0

       job_technician  job_unemployed  marital_married  marital_single
\
1                   1               0                0               1

2                   0               0                1               0

3                   0               0                1               0

4                   0               0                0               1

5                   0               0                1               0

...               ...             ...              ...             ...

45196               0               0                0               1

45197               0               0                0               1

45198               0               0                1               0

45202               0               0                0               1

45209               0               0                1               0


       education_secondary  education_tertiary  default_yes
housing_yes  \
1                        1                   0            0
1
2                        1                   0            0
1
3                        1                   0            0
1
4                        1                   0            0
0
5                        0                   1            0
1
...                    ...                 ...          ...            .
..
45196                    1                   0            0
0
45197                    1                   0            0
1
45198                    0                   1            0
0
45202                    1                   0            0
0
45209                    1                   0            0
```

```
0

       loan_yes
1             0
2             1
3             0
4             0
5             0
...         ...
45196         0
45197         0
45198         0
45202         0
45209         0

[28190 rows x 17 columns]
```

```
newdf=pd.concat([df,df1],axis=1)
newdf
```

```
        age           job  marital  education default  balance housing 
loan  \
1      44.0    technician   single  secondary      no     29.0     yes 
no   
2      33.0  entrepreneur  married  secondary      no      2.0     yes 
yes  
3      47.0   blue-collar  married  secondary      no   1506.0     yes 
no   
4      33.0   blue-collar   single  secondary      no      1.0      no 
no   
5      35.0    management  married   tertiary      no    231.0     yes 
no   
...     ...           ...      ...        ...     ...      ...     ... 
...  
45196  25.0       student   single  secondary      no    358.0      no 
no   
45197  36.0    management   single  secondary      no   1511.0     yes 
no   
45198  37.0    management  married   tertiary      no   1428.0      no 
no   
45202  34.0        admin.   single  secondary      no    557.0      no 
no   
45209  57.0   blue-collar  married  secondary      no    668.0      no 
no   

       day month  ...  job_student  job_technician  job_unemployed  \
1        5   may  ...            0               1               0   
2        5   may  ...            0               0               0   
3        5   may  ...            0               0               0   
4        5   may  ...            0               0               0   
```

```
5         5   may  ...            0              0              0
...     ...   ...  ...          ...            ...            ...
45196    16   nov  ...            1              0              0
45197    16   nov  ...            0              0              0
45198    16   nov  ...            0              0              0
45202    17   nov  ...            0              0              0
45209    17   nov  ...            0              0              0

       marital_married marital_single  education_secondary  \
1                    0              1                    1
2                    1              0                    1
3                    1              0                    1
4                    0              1                    1
5                    1              0                    0
...                ...            ...                  ...
45196                0              1                    1
45197                0              1                    1
45198                1              0                    0
45202                0              1                    1
45209                1              0                    1

       education_tertiary  default_yes  housing_yes  loan_yes
1                       0            0            1         0
2                       0            0            1         1
3                       0            0            1         0
4                       0            0            0         0
5                       1            0            1         0
...                   ...          ...          ...       ...
45196                   0            0            0         0
45197                   0            0            1         0
45198                   1            0            0         0
45202                   0            0            0         0
45209                   0            0            0         0

[28190 rows x 32 columns]
```

```
newdf1=newdf.drop(['job', 'marital', 'education', 'default', 
'housing', 'loan'],axis=1)
newdf1
```

```
        age  balance  day month  duration  campaign  pdays  previous  
y  \
1      44.0     29.0    5   may       151         1     -1         0  
no
2      33.0      2.0    5   may        76         1     -1         0  
no
3      47.0   1506.0    5   may        92         1     -1         0  
no
4      33.0      1.0    5   may       198         1     -1         0  
no
```

```
5       35.0    231.0    5   may       139          1     -1          0
no
...      ...      ...  ...   ...       ...        ...    ...        ...
...
45196  25.0    358.0   16   nov       330          1     -1          0
yes
45197  36.0   1511.0   16   nov       270          1     -1          0
yes
45198  37.0   1428.0   16   nov       333          2     -1          0
no
45202  34.0    557.0   17   nov       224          1     -1          0
yes
45209  57.0    668.0   17   nov       508          4     -1          0
no

       job_blue-collar  ...  job_student  job_technician
job_unemployed  \
1                    0  ...            0               1
0
2                    0  ...            0               0
0
3                    1  ...            0               0
0
4                    1  ...            0               0
0
5                    0  ...            0               0
0
...                ...  ...          ...             ...               .
..
45196                0  ...            1               0
0
45197                0  ...            0               0
0
45198                0  ...            0               0
0
45202                0  ...            0               0
0
45209                1  ...            0               0
0

       marital_married  marital_single  education_secondary  \
1                    0               1                    1
2                    1               0                    1
3                    1               0                    1
4                    0               1                    1
5                    1               0                    0
...                ...             ...                  ...
45196                0               1                    1
45197                0               1                    1
```

```
45198                1           0                    0
45202                0           1                    1
45209                1           0                    1

       education_tertiary  default_yes  housing_yes  loan_yes
1                       0            0            1         0
2                       0            0            1         1
3                       0            0            1         0
4                       0            0            0         0
5                       1            0            1         0
...                   ...          ...          ...       ...
45196                   0            0            0         0
45197                   0            0            1         0
45198                   1            0            0         0
45202                   0            0            0         0
45209                   0            0            0         0

[28190 rows x 26 columns]
```

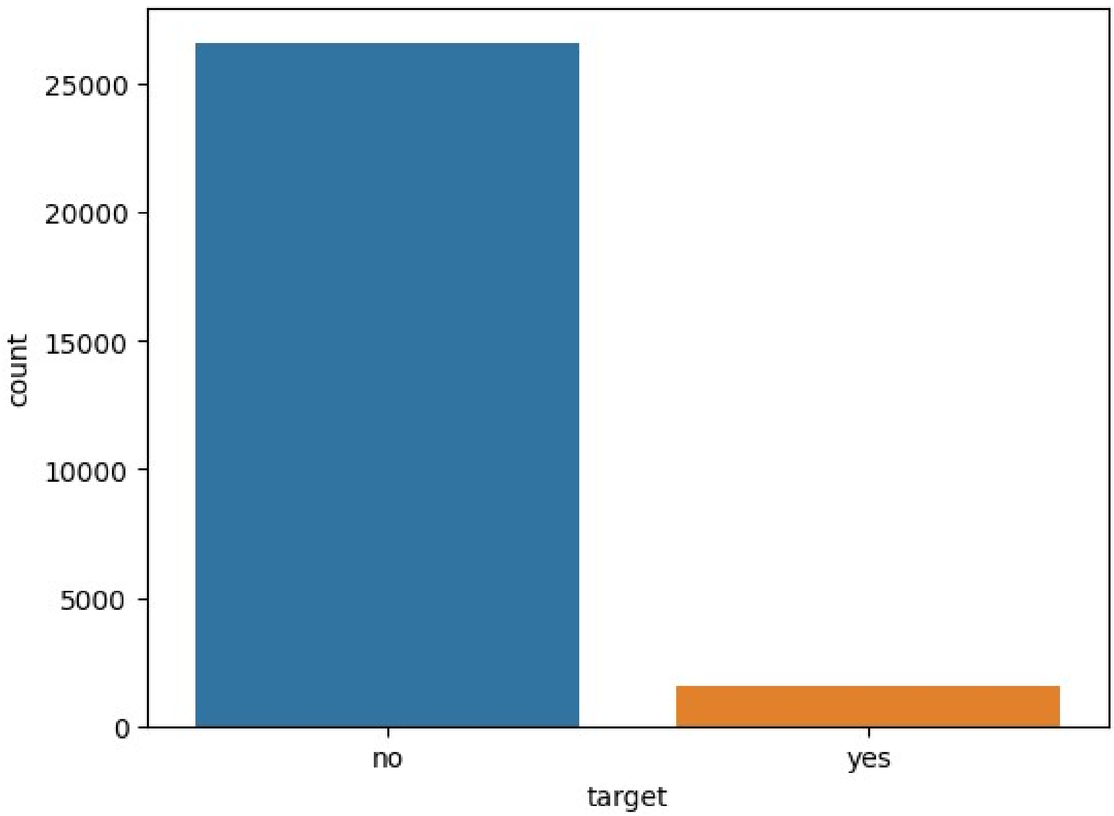
```
newdf1['month'] =
df['month'].map({'jan':1,'feb':2,'mar':3,'apr':4,'may':5,'jun':6,'jul'
:7,'aug':8,'sep':9,'oct':10,'nov':11,'dec':12})
#manual encoding for months to keep months as per numerical order
```

SEPARATING INDEPENDENT AND DEPENDENT VARIABLES

```
x = newdf1.drop('y', axis=1)
y = newdf1['y']
```

HANDLING IMBALANCED DATASET

```
sns.countplot(x=df['y'])
plt.xlabel('target')

df['y'].value_counts()

no     26593
yes     1597
Name: y, dtype: int64
```




```
from imblearn.over_sampling import SMOTE

smote = SMOTE(sampling_strategy='auto',random_state=42)
x_balanced,y_balanced=smote.fit_resample(x,y)
y_balanced.value_counts()

no     26593
yes    26593
Name: y, dtype: int64
```

SEPARATING TRAINING DATA & TESTING DATA

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x_balanced,y_balanced,t
est_size=0.30,random_state=42)
```

NORMALIZATION

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(x_train)
x_train=scaler.transform(x_train)
x_test=scaler.transform(x_test)
```

MODEL CREATION

```
from sklearn.neighbors import KNeighborsClassifier
knn1=KNeighborsClassifier()
param={'n_neighbors':[3,5,7,9],'weights':['uniform','distance']}
```

GRIDSEARCHCV

```
from sklearn.model_selection import GridSearchCV
clf=GridSearchCV(knn1,param,cv=10,scoring='accuracy')
clf.fit(x_train,y_train)
print(clf.best_params_)
```

```
{'n_neighbors': 3, 'weights': 'distance'}
```

```
#Model creation
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=3,weights='distance')
knn.fit(x_train,y_train)
y_prediction=knn.predict(x_test)
y_prediction
```

```
array(['yes', 'no', 'no', ..., 'no', 'yes', 'no'], dtype=object)
```

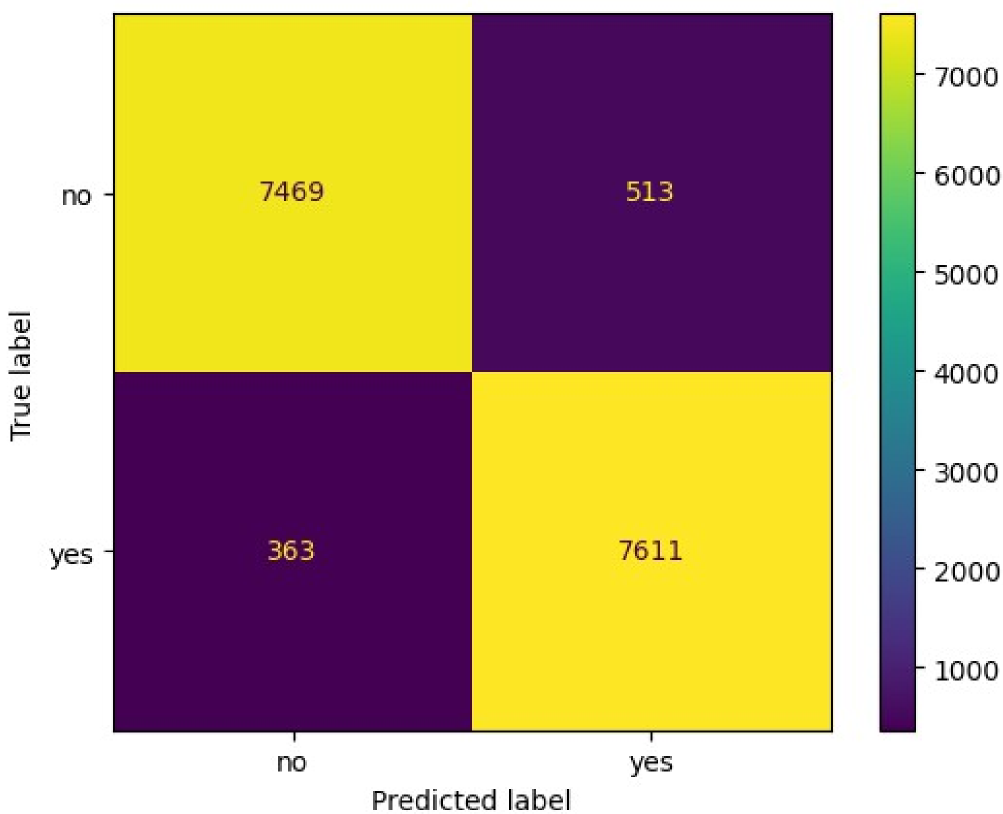
PERFORMANCE EVALUATION

```
from sklearn.metrics import
accuracy_score,confusion_matrix,classification_report,ConfusionMatrixD
isplay
#confusion matrix
matr=confusion_matrix(y_test,y_prediction)
print(matr)
```

```
[[7469  513]
 [ 363 7611]]
```

```
#accuracy score
score=accuracy_score(y_test,y_prediction)
score
```

```
0.9450990223113562

#classification report
report=classification_report(y_test,y_prediction)
print(report)

              precision    recall  f1-score   support

          no       0.95      0.94      0.94      7982
         yes       0.94      0.95      0.95      7974

    accuracy                           0.95     15956
   macro avg       0.95      0.95      0.95     15956
weighted avg       0.95      0.95      0.95     15956


#confusion matrix display
labels=['no','yes']
cmd=ConfusionMatrixDisplay(matr,display_labels=labels)
cmd.plot()

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 
0x7bb7b4270580>
```



```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import BernoulliNB
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import
confusion_matrix,accuracy_score,classification_report

knn=KNeighborsClassifier(n_neighbors=7)
model2 = RandomForestClassifier(criterion =
'entropy',n_estimators=100,random_state=33)
model3 = DecisionTreeClassifier(criterion = 'entropy')
base=BernoulliNB()
model=SVC()
lst=[knn,model2,base,model,model3]

for i in lst:
  print(i)
  i.fit(x_train,y_train)
  y_pred=i.predict(x_test)
  print(confusion_matrix(y_test,y_pred))
  print(accuracy_score(y_test,y_pred))
  print(classification_report(y_test,y_pred))
  print('*'*100)
```

```
KNeighborsClassifier(n_neighbors=7)
[[7435  547]
 [ 464 7510]]
0.936638255201805
              precision    recall  f1-score   support

          no       0.94      0.93      0.94      7982
         yes       0.93      0.94      0.94      7974

    accuracy                           0.94     15956
   macro avg       0.94      0.94      0.94     15956
weighted avg       0.94      0.94      0.94     15956

**********************************************************************
******************************
RandomForestClassifier(criterion='entropy', random_state=33)
[[7723  259]
 [ 340 7634]]
0.9624592629731762
              precision    recall  f1-score   support

          no       0.96      0.97      0.96      7982
         yes       0.97      0.96      0.96      7974

    accuracy                           0.96     15956
```

```
   macro avg       0.96      0.96      0.96     15956
weighted avg       0.96      0.96      0.96     15956

**********************************************************************
******************************
BernoulliNB()
[[7210  772]
 [ 869 7105]]
0.8971546753572324
              precision    recall  f1-score   support

          no       0.89      0.90      0.90      7982
         yes       0.90      0.89      0.90      7974

    accuracy                           0.90     15956
   macro avg       0.90      0.90      0.90     15956
weighted avg       0.90      0.90      0.90     15956

**********************************************************************
******************************
SVC()
[[7578  404]
 [ 650 7324]]
0.9339433441965405
              precision    recall  f1-score   support

          no       0.92      0.95      0.93      7982
         yes       0.95      0.92      0.93      7974

    accuracy                           0.93     15956
   macro avg       0.93      0.93      0.93     15956
weighted avg       0.93      0.93      0.93     15956

**********************************************************************
******************************
DecisionTreeClassifier(criterion='entropy')
[[7364  618]
 [ 476 7498]]
0.9314364502381549
              precision    recall  f1-score   support

          no       0.94      0.92      0.93      7982
         yes       0.92      0.94      0.93      7974

    accuracy                           0.93     15956
   macro avg       0.93      0.93      0.93     15956
weighted avg       0.93      0.93      0.93     15956

**********************************************************************
******************************
```