Problem Statement

BANK MARKETING: Predicting Whether The Customer Will Subscribe To Term Deposit (FIXED DEPOSIT) or not.

Problem Statement: Business Use Case There has been a revenue decline for a Portuguese bank and they would like to know what actions to take. After investigation, they found out that the root cause is that their clients are not depositing as frequently as before. Knowing that term deposits allow banks to hold onto a deposit for a specific amount of time, so banks can invest in higher gain financial products to make a profit. In addition, banks also hold better chance to persuade term deposit clients into buying other products such as funds or insurance to further increase their revenues. As a result, the Portuguese bank would like to identify existing clients that have higher chance to subscribe for a term deposit and focus marketing efforts on such clients.

Problem Statement Your client is a retail banking institution. Term deposits are a major source of income for a bank. A term deposit is a cash investment held at a financial institution. Your money is invested for an agreed rate of interest over a fixed amount of time, or term. The bank has various outreach plans to sell term deposits to their customers such as email marketing, advertisements, telephonic marketing and digital marketing. Telephonic marketing campaigns still remain one of the most effective way to reach out to people. However, they require huge investment as large call centers are hired to actually execute these campaigns. Hence, it is crucial to identify the customers most likely to convert beforehand so that they can be specifically targeted via call.

You are provided with the client data such as : age of the client, their job type, their marital status, etc. Along with the client data, you are also provided with the information of the call such as the duration of the call, day and month of the call, etc. Given this information, your task is to predict if the client will subscribe to term deposit.

About The Dataset The dataset is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal of this dataset is to predict if the client or the customer of polish banking institution will subscribe a term deposit product of the bank or not.

You are provided with following 2 files:

1. train.csv : Use this dataset to train the model. This file contains all the client and call details as well as the target variable “subscribed”. You have to train your model using this file.

2. test.csv : Use the trained model to predict whether a new set of clients will subscribe the term deposit.

Dataset Attributes Here is the description of all the variables :

Variable: Definition ID: Unique client ID age: Age of the client job: Type of job marital: Marital status of the client education: Education level default: Credit in default. housing: Housing loan loan: Personal loan contact: Type of communication month: Contact month day_of_week: Day of week of contact duration: Contact duration campaign: number of contacts performed during this campaign to the client pdays: number of days that passed by after the client was last contacted previous: number of contacts performed before this campaign poutcome: outcome of the previous marketing campaign Output variable (desired target): Subscribed (target): has the client subscribed a term deposit? (YES/NO)

Importing dependencies

In [161…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Loading the data

In [162…
```
train=pd.read_csv('termdeposit_train.csv')
train.head()
```

Out[162]:

	ID	age	job	marital	education	default	balance	housing	loan	contact	day	month	dura
0	26110	56	admin.	married	unknown	no	1933	no	no	telephone	19	nov	
1	40576	31	unknown	married	secondary	no	3	no	no	cellular	20	jul	
2	15320	27	services	married	secondary	no	891	yes	no	cellular	18	jul	
3	43962	57	management	divorced	tertiary	no	3287	no	no	cellular	22	jun	
4	29842	31	technician	married	secondary	no	119	yes	no	cellular	4	feb	

In [163…
```
test=pd.read_csv('termdeposit_test.csv')
test.head()
```

Out[163]:

	ID	age	job	marital	education	default	balance	housing	loan	contact	day	month	duratio
0	38441	32	services	married	secondary	no	118	yes	no	cellular	15	may	2
1	40403	78	retired	divorced	primary	no	2787	no	no	telephone	1	jul	37
2	3709	31	self-employed	single	tertiary	no	144	yes	no	unknown	16	may	67
3	37422	57	services	single	primary	no	3777	yes	no	telephone	13	may	6
4	12527	45	blue-collar	divorced	secondary	no	-705	no	yes	unknown	3	jul	11

Shape of data

In [164…
```
train.shape
```

Out[164]:
```
(31647, 18)
```

In [165…
```
test.shape
```

Out[165]:
```
(13564, 17)
```

Coulumns

In [166…
```
train.columns
```
Out[166]:
```
Index(['ID', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'subscribed'],
      dtype='object')
```
In [167…
```
test.columns
```
Out[167]:
```
Index(['ID', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome'],
      dtype='object')
```
Here we dont have column 'subscribed'(target)

Data info

In [168…
```
train.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31647 entries, 0 to 31646
Data columns (total 18 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   ID          31647 non-null  int64 
 1   age         31647 non-null  int64 
 2   job         31647 non-null  object
 3   marital     31647 non-null  object
 4   education   31647 non-null  object
 5   default     31647 non-null  object
 6   balance     31647 non-null  int64 
 7   housing     31647 non-null  object
 8   loan        31647 non-null  object
 9   contact     31647 non-null  object
 10  day         31647 non-null  int64 
 11  month       31647 non-null  object
 12  duration    31647 non-null  int64 
 13  campaign    31647 non-null  int64 
 14  pdays       31647 non-null  int64 
 15  previous    31647 non-null  int64 
 16  poutcome    31647 non-null  object
 17  subscribed  31647 non-null  object
dtypes: int64(8), object(10)
memory usage: 4.3+ MB
```
In [169…
```
test.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13564 entries, 0 to 13563
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   ID         13564 non-null  int64 
 1   age        13564 non-null  int64 
 2   job        13564 non-null  object
 3   marital    13564 non-null  object
 4   education  13564 non-null  object
 5   default    13564 non-null  object
 6   balance    13564 non-null  int64 
 7   housing    13564 non-null  object
 8   loan       13564 non-null  object
 9   contact    13564 non-null  object
 10  day        13564 non-null  int64 
 11  month      13564 non-null  object
 12  duration   13564 non-null  int64 
```

```
 13  campaign   13564 non-null  int64
 14  pdays      13564 non-null  int64
 15  previous   13564 non-null  int64
 16  poutcome   13564 non-null  object
dtypes: int64(8), object(9)
memory usage: 1.8+ MB
```

Checking null value

In [170…
```
train.isnull().sum()
```

Out[170]:
```
ID            0
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
subscribed    0
dtype: int64
```

we dont have any null value in train dataset

In [171…
```
test.isnull().sum()
```

Out[171]:
```
ID           0
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
dtype: int64
```

we dont have any null value in test dataset as well.

Checking for Duplicates

In [172…
```
## Checking for duplicates on train data
train.duplicated().sum()
```

Out[172]:
```
0
```

In [173…
```
## Checking for duplicates on test data
test.duplicated().sum()
```
Out[173]:

0

Replacing whitespaces with null if any

In [174…
```
train.replace([' ','  '], ['',''], inplace=True)
test.replace([' ','  '], ['',''], inplace=True)
```
In [175…
```
train.isnull().sum().sum()
```
Out[175]:

0

In [176…
```
train.isnull().sum().sum()
```
Out[176]:

0

we dont have any whitespaces in our data.

Data Cleaning

In [177…
```
# Droping ID column as it has no relevance in prediction
train.drop('ID', axis=1, inplace=True)
train.head()
```
Out[177]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	ca
0	56	admin.	married	unknown	no	1933	no	no	telephone	19	nov	44	
1	31	unknown	married	secondary	no	3	no	no	cellular	20	jul	91	
2	27	services	married	secondary	no	891	yes	no	cellular	18	jul	240	
3	57	management	divorced	tertiary	no	3287	no	no	cellular	22	jun	867	
4	31	technician	married	secondary	no	119	yes	no	cellular	4	feb	380	

In [178…
```
test.drop('ID', axis=1, inplace=True)
test.head()
```
Out[178]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	camp
0	32	services	married	secondary	no	118	yes	no	cellular	15	may	20	
1	78	retired	divorced	primary	no	2787	no	no	telephone	1	jul	372	
2	31	self-employed	single	tertiary	no	144	yes	no	unknown	16	may	676	
3	57	services	single	primary	no	3777	yes	no	telephone	13	may	65	
4	45	blue-collar	divorced	secondary	no	-705	no	yes	unknown	3	jul	111	

In [179…
```
train.describe()
```
Out[179]:

	age	balance	day	duration	campaign	pdays	previous

count	31647.000000	31647.000000	31647.000000	31647.000000	31647.000000	31647.000000	31647.000000
mean	40.957247	1363.890258	15.835466	258.113534	2.765697	39.576042	0.574272
std	10.625134	3028.304293	8.337097	257.118973	3.113830	99.317592	2.422529
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	73.000000	8.000000	104.000000	1.000000	-1.000000	0.000000
50%	39.000000	450.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1431.000000	21.000000	318.500000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

75% people younger thamn 48 yeras and oldest person is of age 95

In [180…

```
test.describe()
```

Out[180]:

	age	balance	day	duration	campaign	pdays	previous
count	13564.000000	13564.000000	13564.000000	13564.000000	13564.000000	13564.000000	13564.000000
mean	40.887128	1358.496535	15.738646	258.278679	2.759510	41.648555	0.594441
std	10.604108	3082.940623	8.288174	258.488648	3.060928	101.985178	1.998193
min	18.000000	-3313.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	71.000000	8.000000	102.000000	1.000000	-1.000000	0.000000
50%	39.000000	445.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1413.250000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	98417.000000	31.000000	3253.000000	58.000000	850.000000	55.000000

Data Analysis

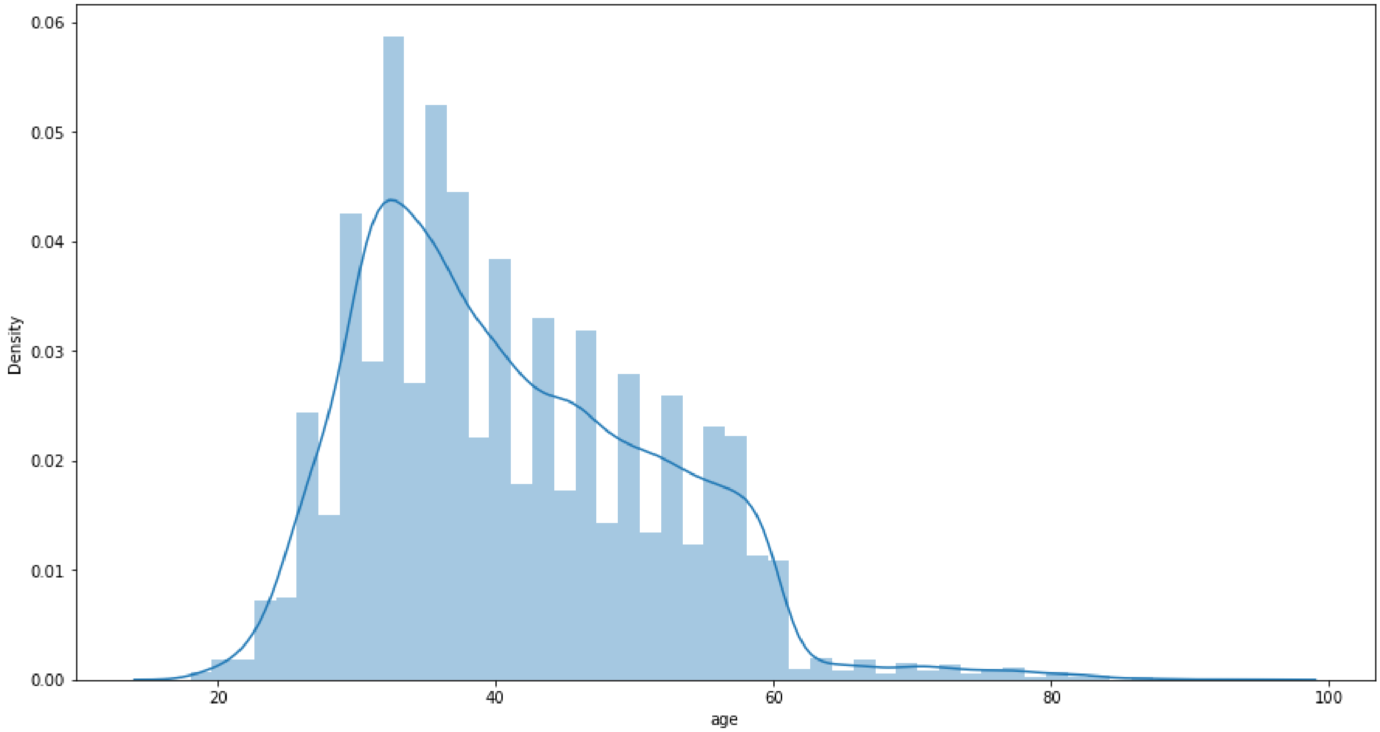
Age Column

In [21]:

```
plt.figure(figsize=(15,8))
sns.distplot(train['age'])
```

Out[21]:

```
<AxesSubplot:xlabel='age', ylabel='Density'>
```

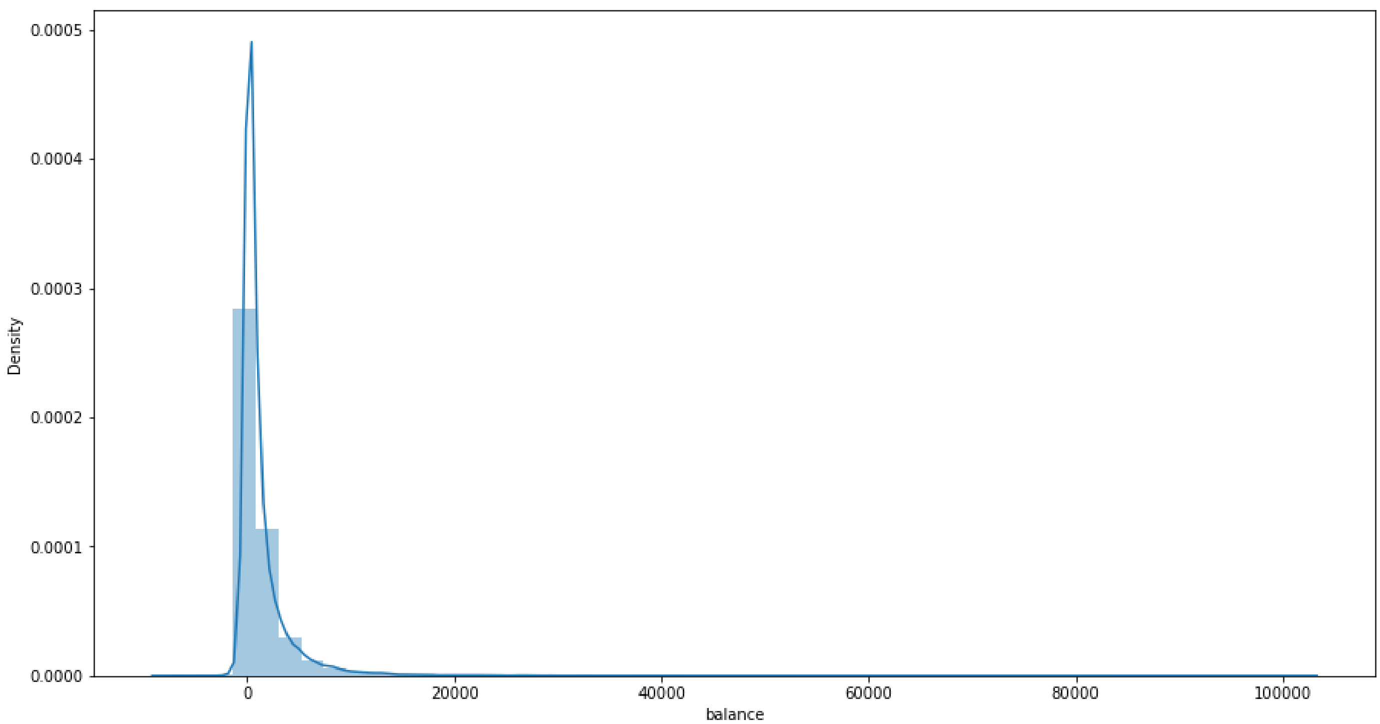


Majority people are between 30-40 years old.

Analysis for Balance column

In [22]:
```
plt.figure(figsize=(15,8))
sns.distplot(train['balance'])
```

Out[22]:
```
<AxesSubplot:xlabel='balance', ylabel='Density'>
```



Most people have balnce between 0-2000

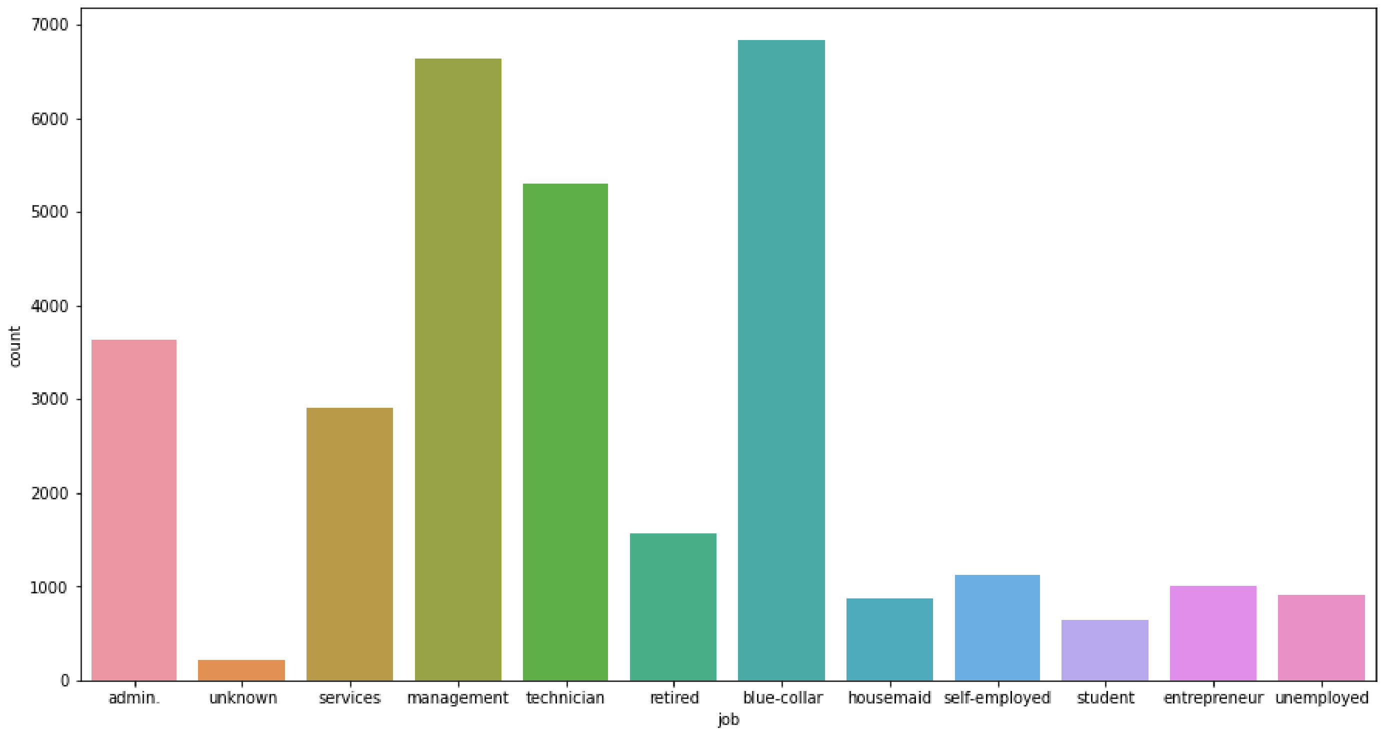
Analysis of Job Column

In [23]:
```
train['job'].value_counts()
```

Out[23]:
```
blue-collar      6842
management       6639
technician       5307
admin.           3631
services         2903
retired          1574
self-employed    1123
entrepreneur     1008
unemployed        905
housemaid         874
student           635
unknown           206
Name: job, dtype: int64
```

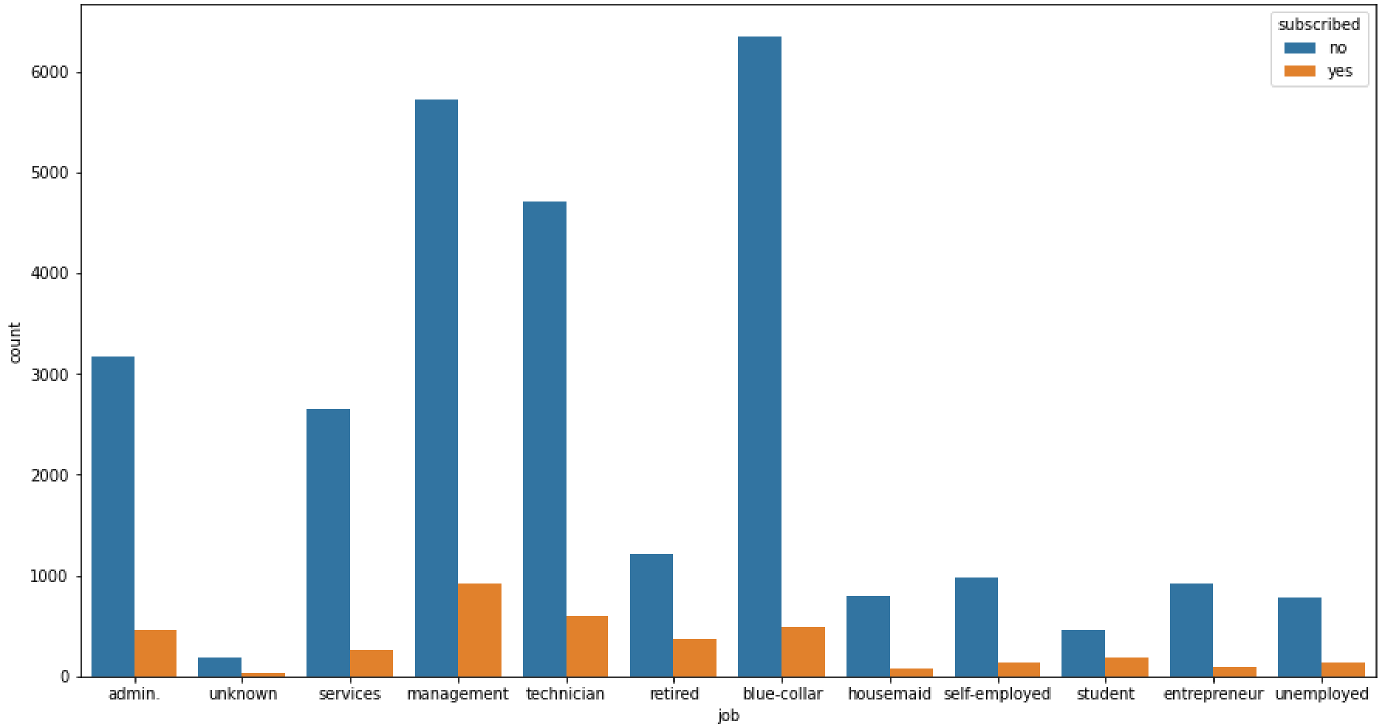
In [24]:
```
# ploting countplot for job column
plt.figure(figsize=(15,8))
sns.countplot(train['job'])
```

Out[24]:
```
<AxesSubplot:xlabel='job', ylabel='count'>
```



In [25]:
```
plt.figure(figsize=(15,8))
sns.countplot(train['job'], hue=train['subscribed'])
```

Out[25]:
```
<AxesSubplot:xlabel='job', ylabel='count'>
```



Majority people have blue color jobs followed by managemnet and technician. But people who have subscribed have job as management and technicion.

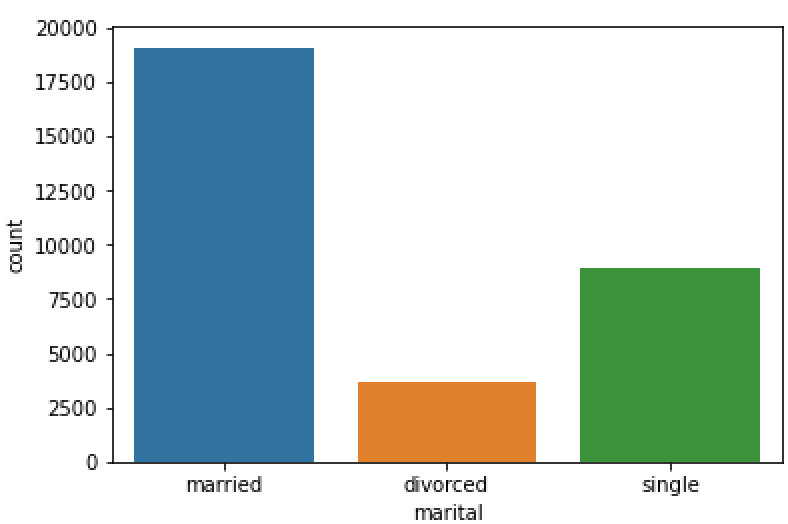
Analysis of marital column

In [26]:
```
train['marital'].value_counts()
```

Out[26]:
```
married     19095
single       8922
divorced     3630
Name: marital, dtype: int64
```

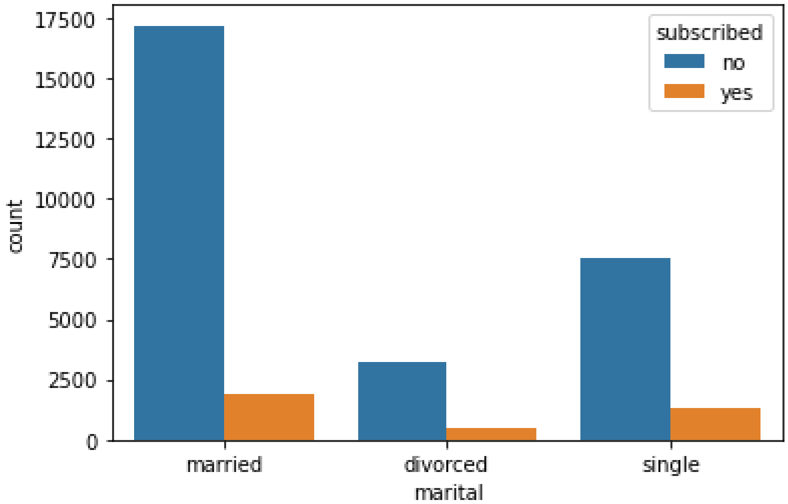
In [27]:
```
# ploting above data in chart for better understanding
sns.countplot(train['marital'])
```

Out[27]:
```
<AxesSubplot:xlabel='marital', ylabel='count'>
```



In [181…:
```
sns.countplot(train['marital'], hue=train['subscribed'])
```

Out[181]:
```
<AxesSubplot:xlabel='marital', ylabel='count'>
```



Majority people are married, also majority people who subscribed are also married.

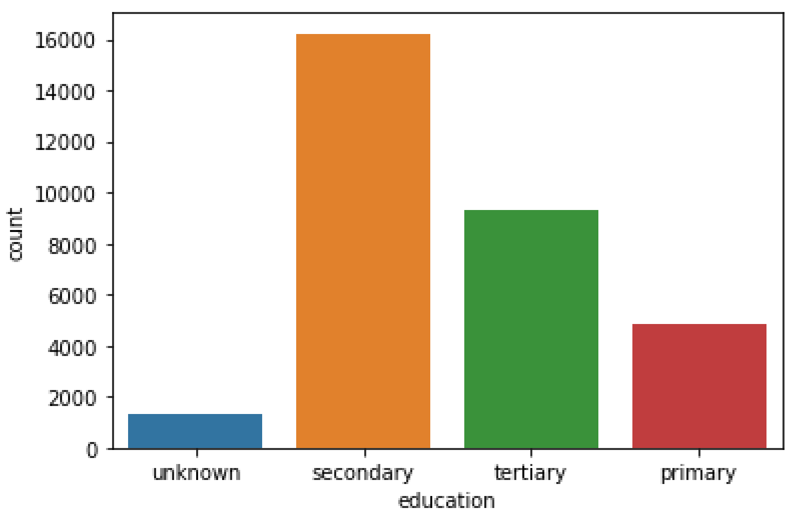
Analysis of Education column

In [28]:
```
train['education'].value_counts()
```

Out[28]:
```
secondary    16224
tertiary      9301
primary       4808
unknown       1314
Name: education, dtype: int64
```

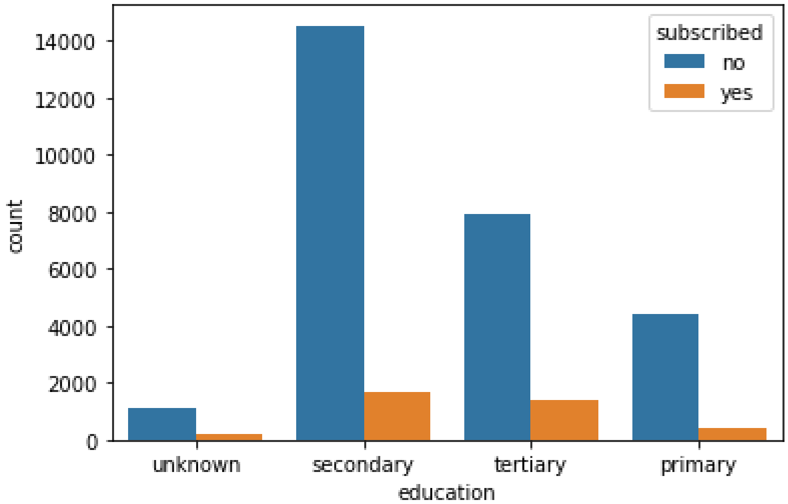
In [29]:
```
sns.countplot(train['education'])
```

Out[29]:
```
<AxesSubplot:xlabel='education', ylabel='count'>
```



In [182…
```
sns.countplot(train['education'], hue=train['subscribed'])
```

Out[182]:
```
<AxesSubplot:xlabel='education', ylabel='count'>
```



Most people have secondary education and majority people who subscribed also have secondary education.

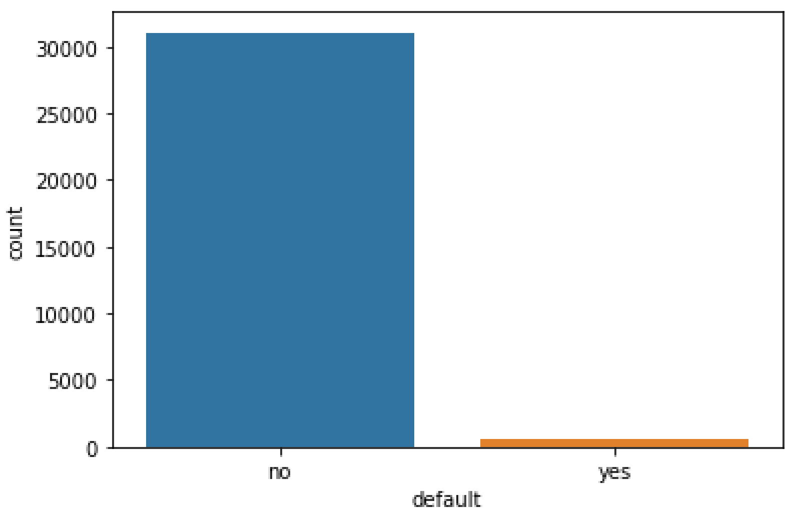
Analysis of default column

In [30]:
```
train['default'].value_counts()
```

Out[30]:
```
no      31062
yes       585
Name: default, dtype: int64
```

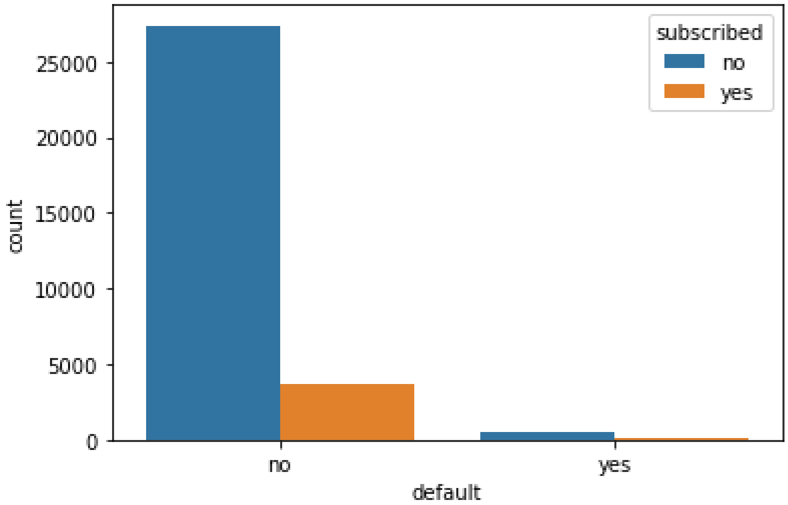
In [31]:
```
sns.countplot(train['default'])
```

Out[31]:
```
<AxesSubplot:xlabel='default', ylabel='count'>
```



In [183…
```
sns.countplot(train['default'], hue=train['subscribed'])
```

Out[183]:
```
<AxesSubplot:xlabel='default', ylabel='count'>
```



Most people have no credit default, also people with no credit default are the majority subscriber.

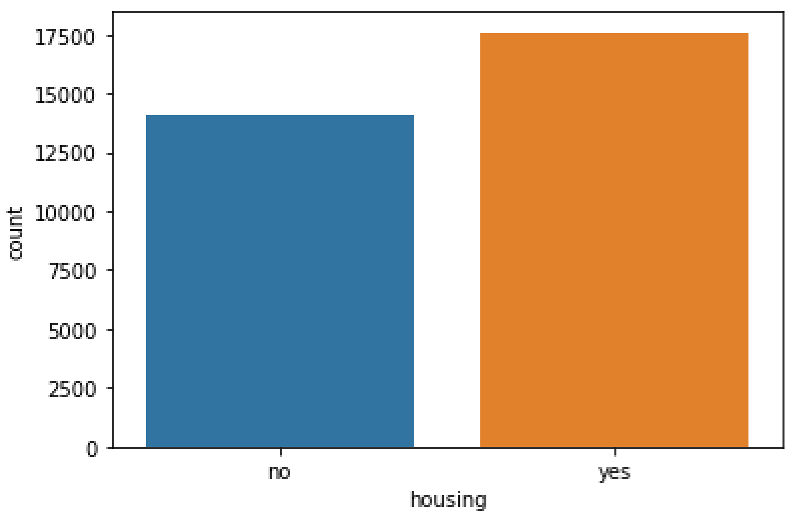
Analysis of housing loan column

In [32]:
```
train['housing'].value_counts()
```

Out[32]:
```
yes    17584
no     14063
Name: housing, dtype: int64
```

In [33]:
```
sns.countplot(train['housing'])
```

Out[33]:
```
<AxesSubplot:xlabel='housing', ylabel='count'>
```



Majority people have housing loan.

Analysis of personal loan column

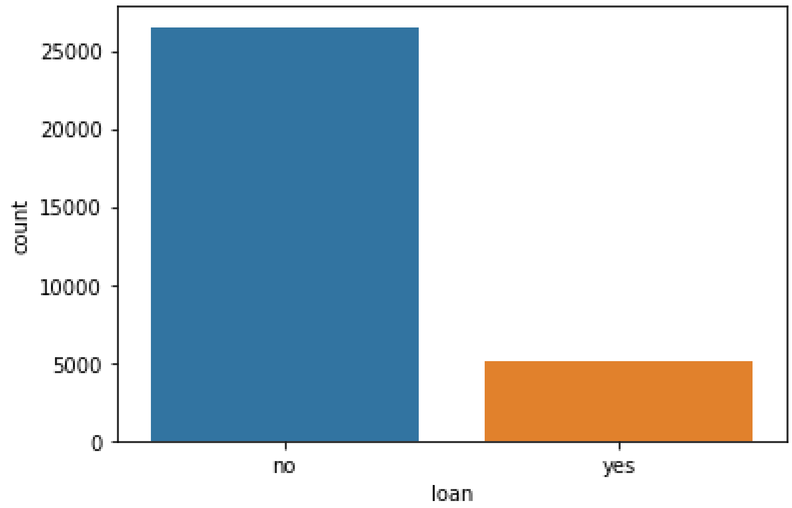
In [34]:
```
train['loan'].value_counts()
```

Out[34]:
```
no     26516
yes     5131
Name: loan, dtype: int64
```

In [35]:
```
sns.countplot(train['loan'])
```

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

Out[35]:



most people dont have personal loan

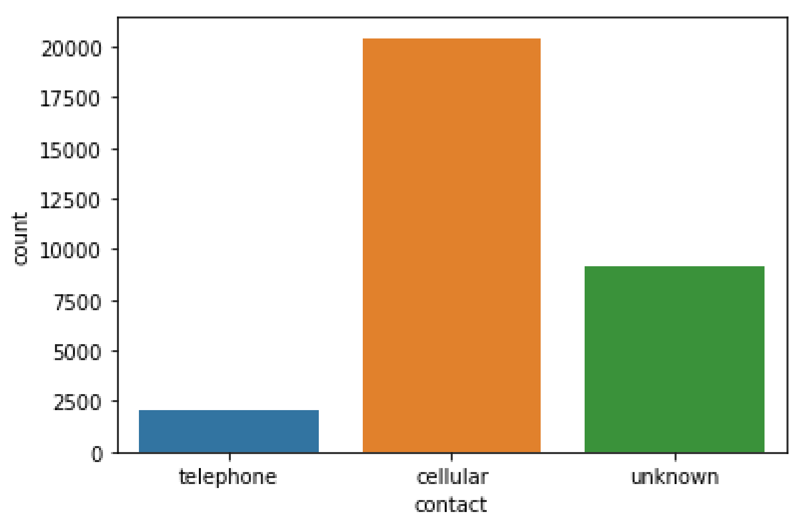
Analysis of contact column

In [36]:
```
train['contact'].value_counts()
```

Out[36]:
```
cellular     20423
unknown       9177
telephone     2047
Name: contact, dtype: int64
```

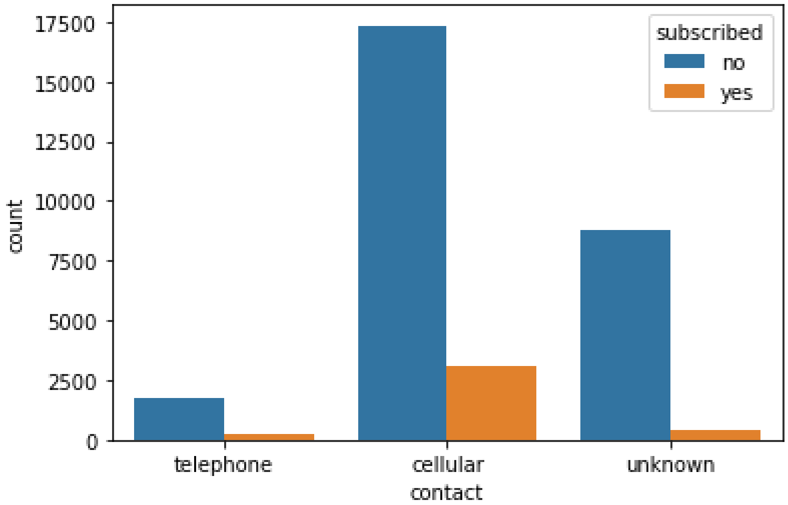
In [37]:
```
sns.countplot(train['contact'])
```

Out[37]:
```
<AxesSubplot:xlabel='contact', ylabel='count'>
```



In [38]:
```
sns.countplot(train['contact'], hue=train['subscribed'])
```

Out[38]:
```
<AxesSubplot:xlabel='contact', ylabel='count'>
```



majority people are contacted through cellular contact and most people who subscribed were contacted through cellular

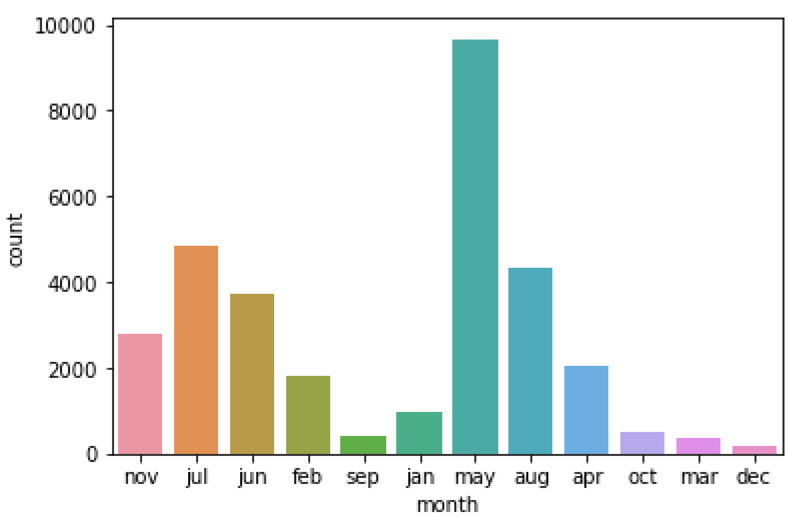
Analysis of month column

In [39]:
```
train['month'].value_counts()
```

Out[39]:
```
may     9669
jul     4844
aug     4333
jun     3738
nov     2783
apr     2055
feb     1827
jan      977
oct      512
sep      410
mar      342
dec      157
Name: month, dtype: int64
```

In [40]:
```
sns.countplot(train['month'])
```

Out[40]:
```
<AxesSubplot:xlabel='month', ylabel='count'>
```

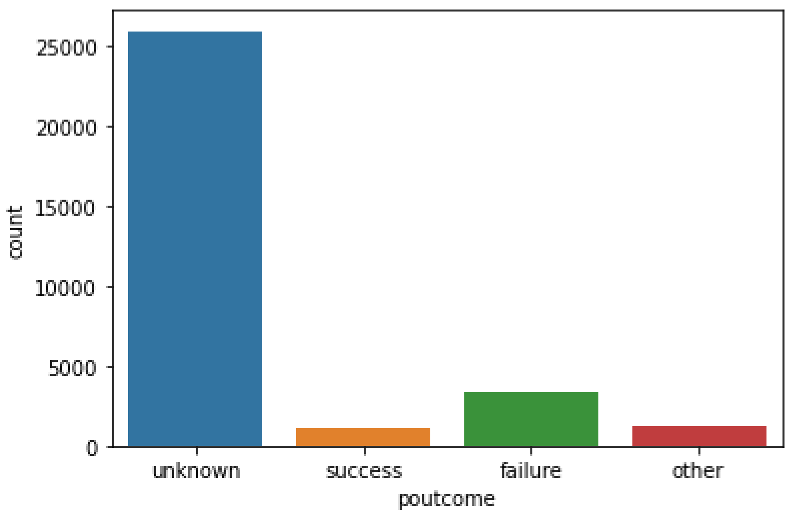


Majority people were contacted in the month May, july, Aug and june

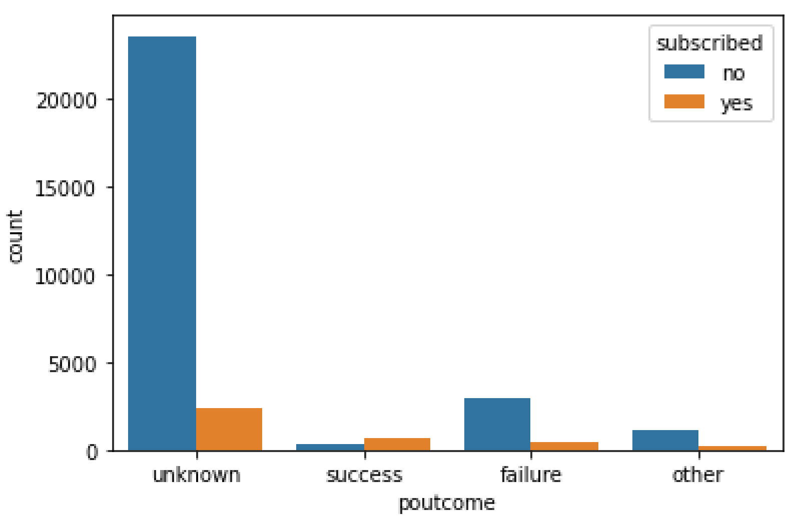
Analysis of poutcome column

In [41]:
```
train['poutcome'].value_counts()
```
Out[41]:
```
unknown     25929
failure      3362
other        1288
success      1068
Name: poutcome, dtype: int64
```

In [42]:
```
sns.countplot(train['poutcome'])
```
Out[42]:
```
<AxesSubplot:xlabel='poutcome', ylabel='count'>
```



In [43]:
```
sns.countplot(train['poutcome'],hue=train['subscribed'])
```
Out[43]:
```
<AxesSubplot:xlabel='poutcome', ylabel='count'>
```



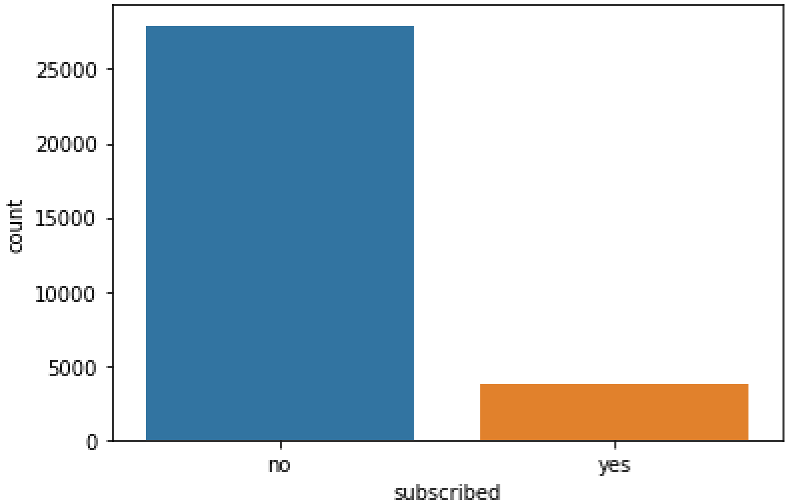
For most people outcome of the previous marketing campaign is unknown

Analysis of Subscribed column

In [44]:
```
train['subscribed'].value_counts()
```
Out[44]:
```
no     27932
yes     3715
Name: subscribed, dtype: int64
```

In [45]:
```
sns.countplot(train['subscribed'])
```

Out[45]: <AxesSubplot:xlabel='subscribed', ylabel='count'>



Most people contacted have not subscribed

Correlation

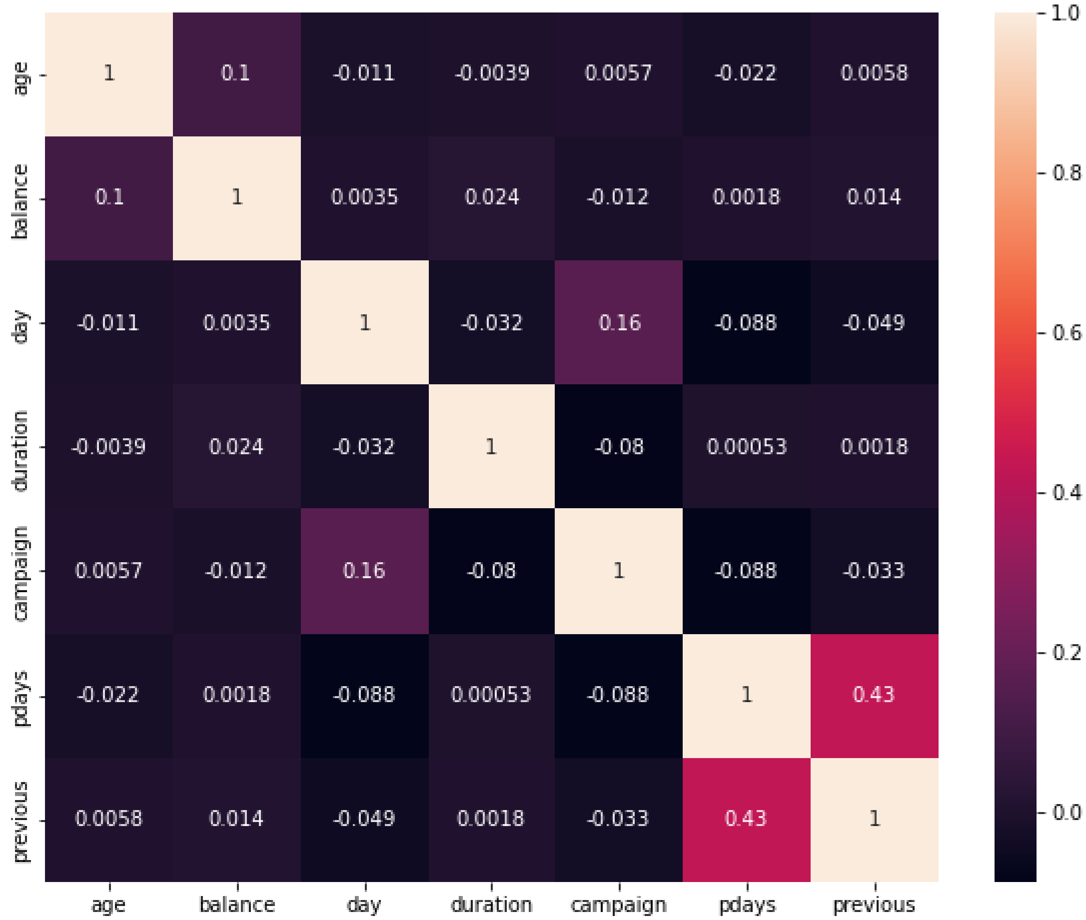
In [46]:
```
train.corr()
```

Out[46]:

	age	balance	day	duration	campaign	pdays	previous
age	1.000000	0.103245	-0.011056	-0.003870	0.005733	-0.021947	0.005761
balance	0.103245	1.000000	0.003461	0.024274	-0.012032	0.001789	0.013843
day	-0.011056	0.003461	1.000000	-0.032288	0.159168	-0.087626	-0.048752
duration	-0.003870	0.024274	-0.032288	1.000000	-0.080305	0.000529	0.001783
campaign	0.005733	-0.012032	0.159168	-0.080305	1.000000	-0.087570	-0.033151
pdays	-0.021947	0.001789	-0.087626	0.000529	-0.087570	1.000000	0.428938
previous	0.005761	0.013843	-0.048752	0.001783	-0.033151	0.428938	1.000000

In [47]:
```
plt.figure(figsize=(10,8))
sns.heatmap(train.corr(), annot=True)
```

Out[47]: <AxesSubplot:>



Encoding

In [48]:
```
train['subscribed'].replace(['yes','no'], [1,0], inplace=True)
```

Deviding Data into feature(x) and target(y)

In [49]:
```
x=train.drop('subscribed',axis=1)
y=train['subscribed']
```

In [50]:
```
cat_columns=[i for i in x.columns if x[i].dtypes=='O']
```

In [51]:
```
cat_columns
```

Out[51]:
```
['job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'poutcome']
```

In [52]:
```
from sklearn.preprocessing import OrdinalEncoder,LabelEncoder
ordinal=OrdinalEncoder()

#using ordinal encoder for independent features
for i in cat_columns:
    x[i]=ordinal.fit_transform(x[i].values.reshape(-1,1))
```

```
    train[i]=ordinal.fit_transform(train[i].values.reshape(-1,1))
    test[i]=ordinal.fit_transform(test[i].values.reshape(-1,1))
```

In [53]:
```
x
```

Out[53]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaig
0	56	0.0	1.0	3.0	0.0	1933	0.0	0.0	1.0	19	9.0	44	
1	31	11.0	1.0	1.0	0.0	3	0.0	0.0	0.0	20	5.0	91	
2	27	7.0	1.0	1.0	0.0	891	1.0	0.0	0.0	18	5.0	240	
3	57	4.0	0.0	2.0	0.0	3287	0.0	0.0	0.0	22	6.0	867	
4	31	9.0	1.0	1.0	0.0	119	1.0	0.0	0.0	4	3.0	380	
...	...	...	...	...	...	...	...	...	...	...	...	...	
31642	29	4.0	2.0	2.0	0.0	0	1.0	0.0	0.0	12	8.0	116	
31643	53	4.0	0.0	2.0	0.0	380	0.0	1.0	0.0	5	6.0	438	
31644	32	4.0	2.0	2.0	0.0	312	0.0	0.0	0.0	7	1.0	37	
31645	57	9.0	1.0	1.0	0.0	225	1.0	0.0	1.0	15	8.0	22	
31646	55	4.0	0.0	1.0	0.0	204	1.0	0.0	0.0	11	5.0	1973	

31647 rows × 16 columns

In [54]:
```
test
```

Out[54]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaigr
0	32	7.0	1.0	1.0	0.0	118	1.0	0.0	0.0	15	8.0	20	6
1	78	5.0	0.0	0.0	0.0	2787	0.0	0.0	1.0	1	5.0	372	1
2	31	6.0	2.0	2.0	0.0	144	1.0	0.0	2.0	16	8.0	676	1
3	57	7.0	2.0	0.0	0.0	3777	1.0	0.0	1.0	13	8.0	65	2
4	45	1.0	0.0	1.0	0.0	-705	0.0	1.0	2.0	3	5.0	111	1
...	...	...	...	...	...	...	...	...	...	...	...	...	..
13559	39	4.0	1.0	2.0	0.0	45	0.0	0.0	0.0	28	1.0	148	4
13560	54	1.0	1.0	0.0	0.0	2281	1.0	0.0	2.0	20	6.0	158	1
13561	35	5.0	1.0	0.0	0.0	285	1.0	0.0	0.0	29	4.0	136	1
13562	29	0.0	2.0	1.0	0.0	464	0.0	0.0	0.0	9	9.0	208	2
13563	29	0.0	1.0	1.0	0.0	2	1.0	0.0	0.0	6	8.0	339	1

13564 rows × 16 columns

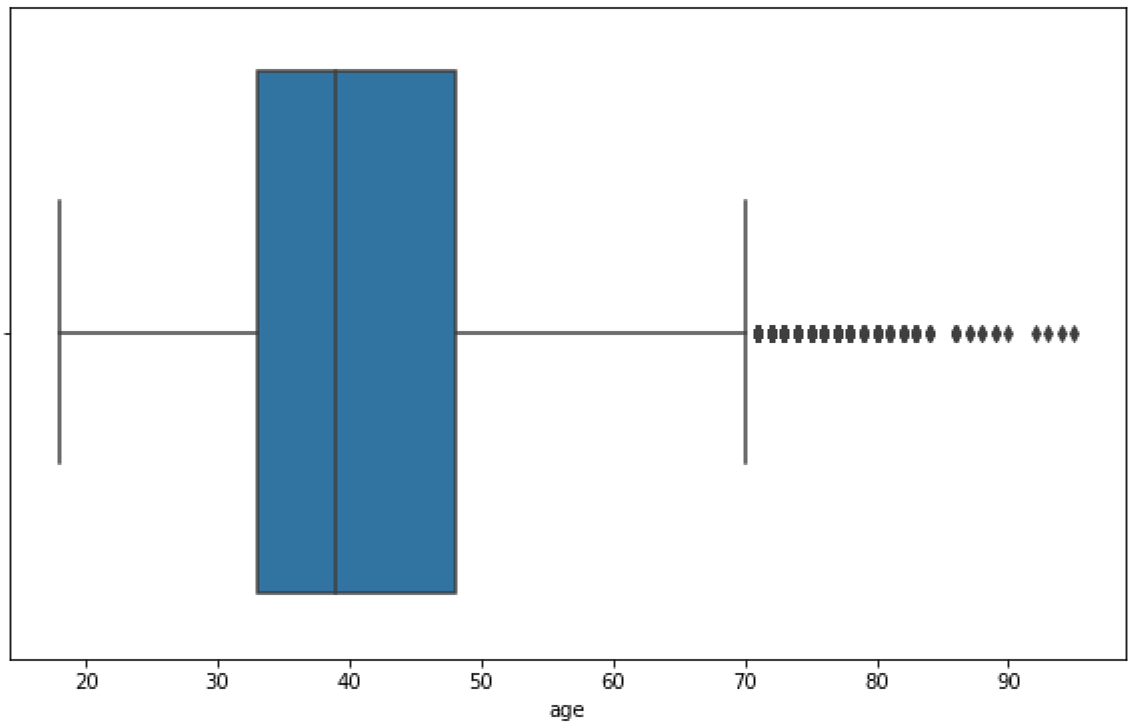
In [55]:
```
y
```

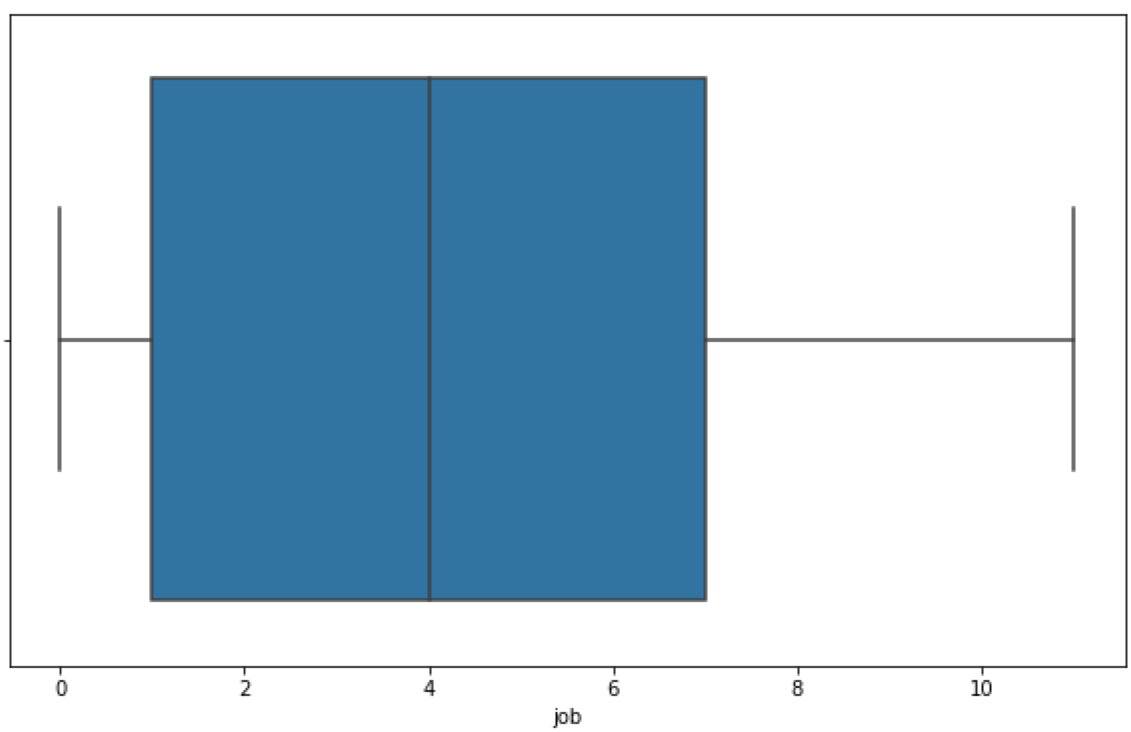
Out[55]:
```
0        0
1        0
2        0
3        1
4        0
        ..
31642    0
```

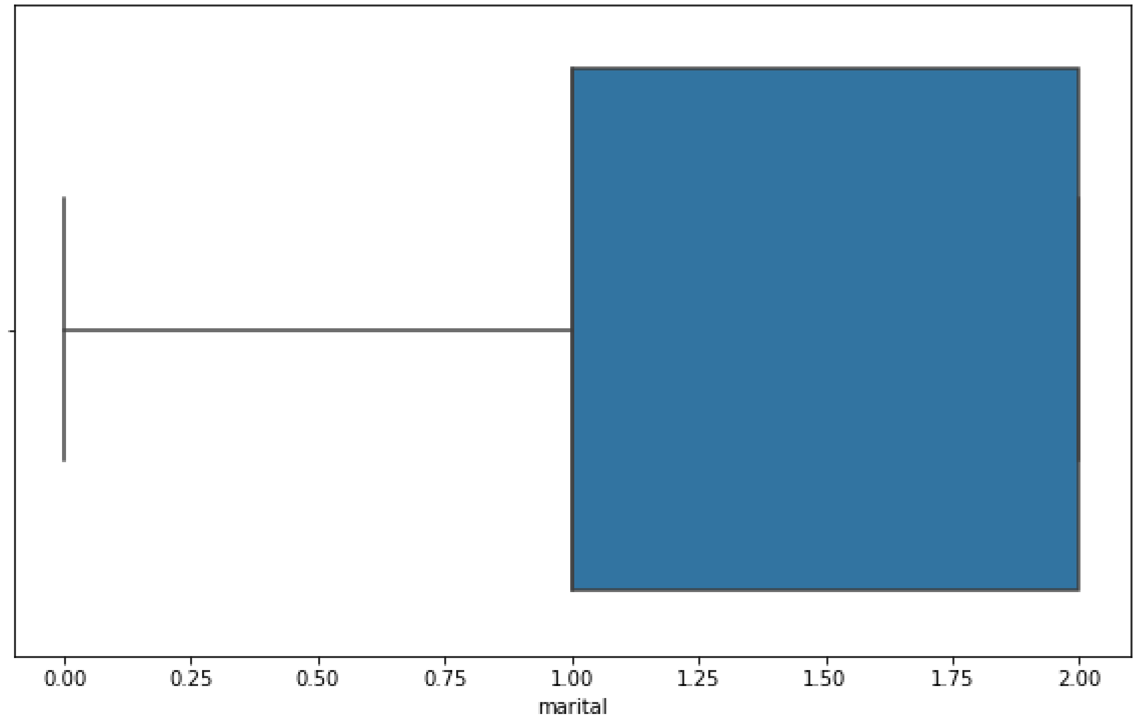
```
31643    1
31644    0
31645    0
31646    1
Name: subscribed, Length: 31647, dtype: int64
```

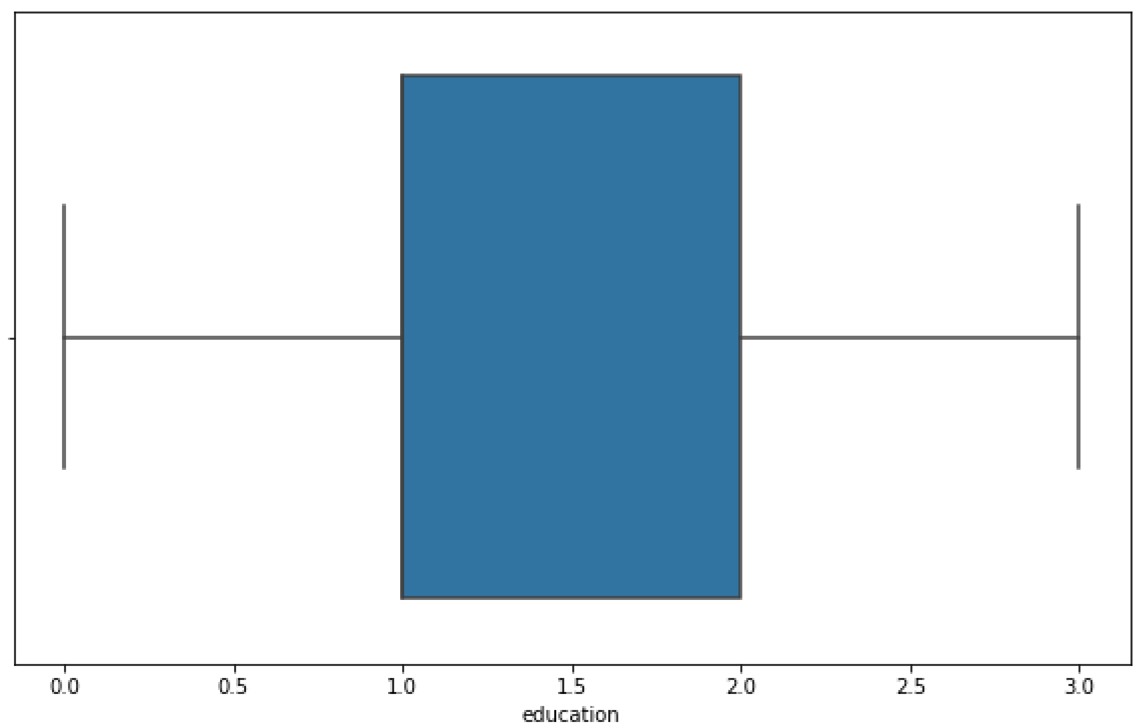
Outliers

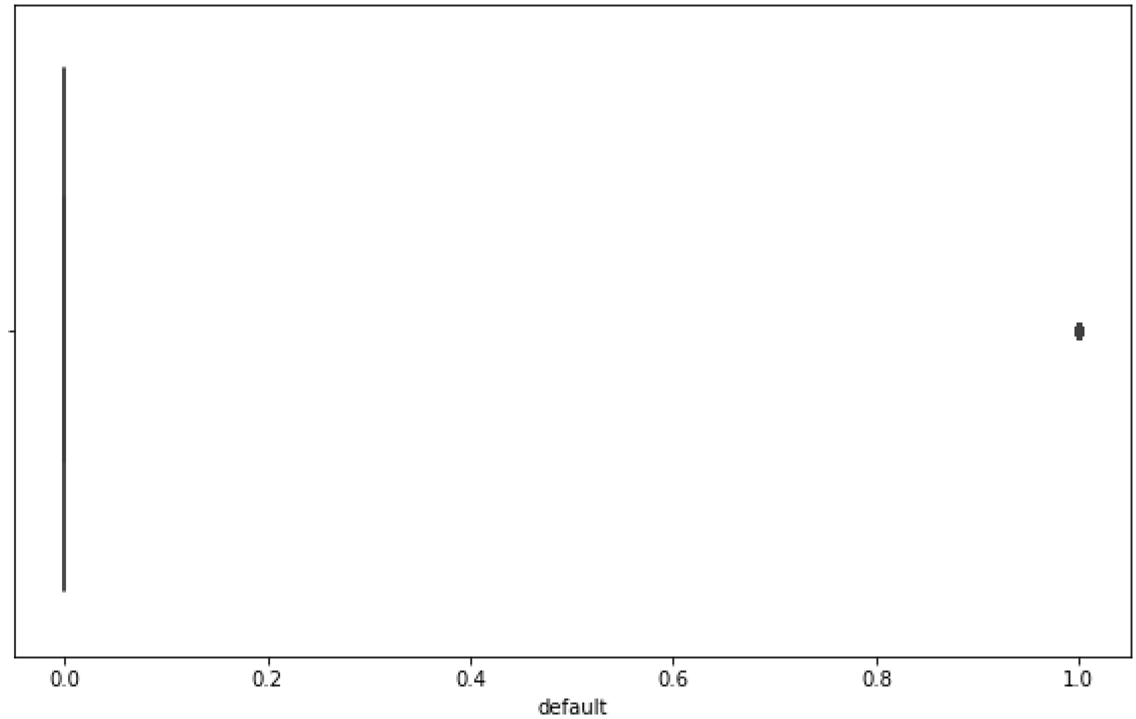
In [56]:
```python
for i in x:
    plt.figure(figsize=(10,6))
    sns.boxplot(train[i])
```



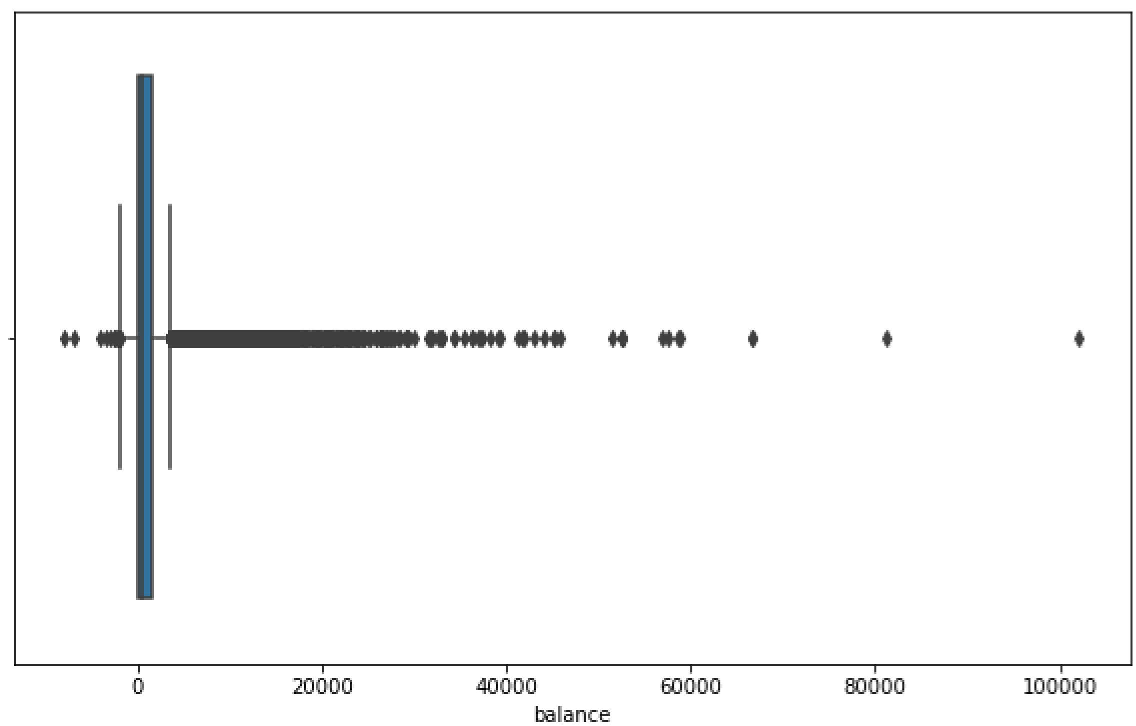



0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
marital

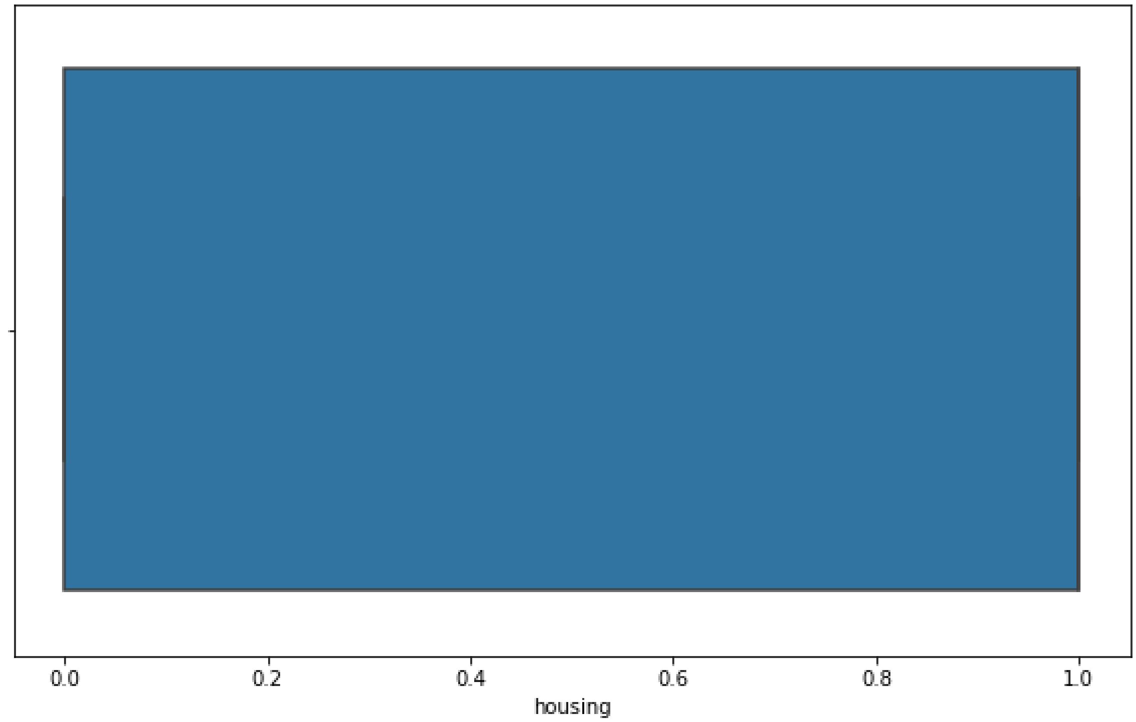

0.0
0.5
1.0
1.5
2.0
2.5
3.0
education

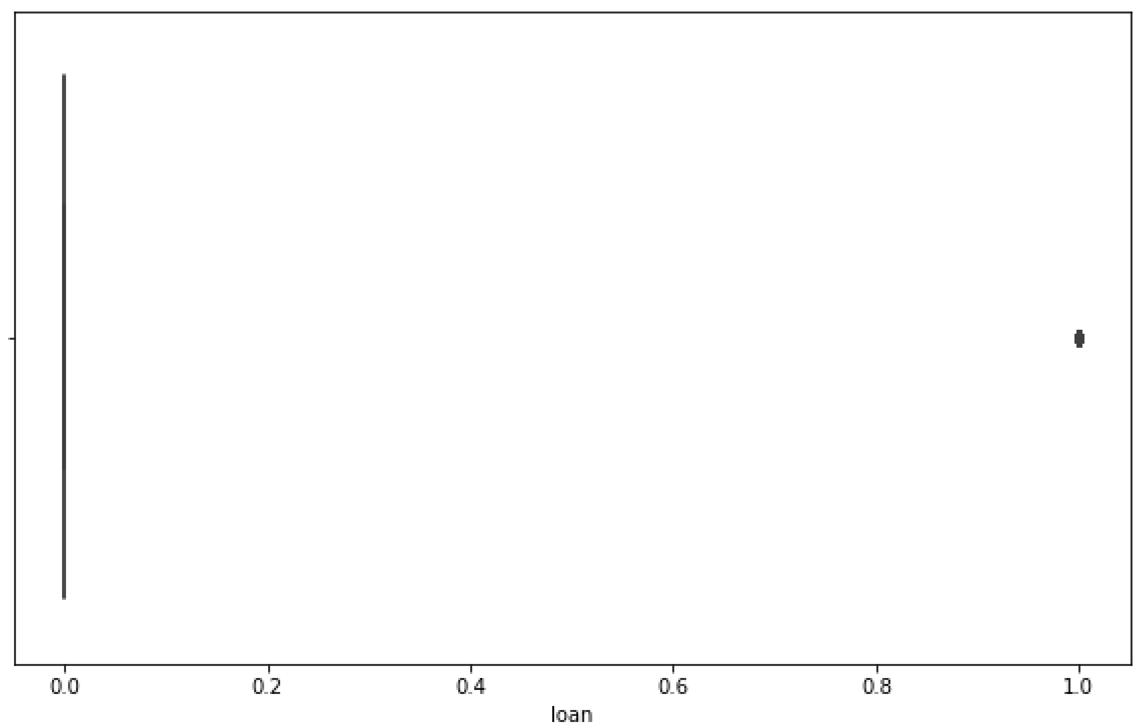


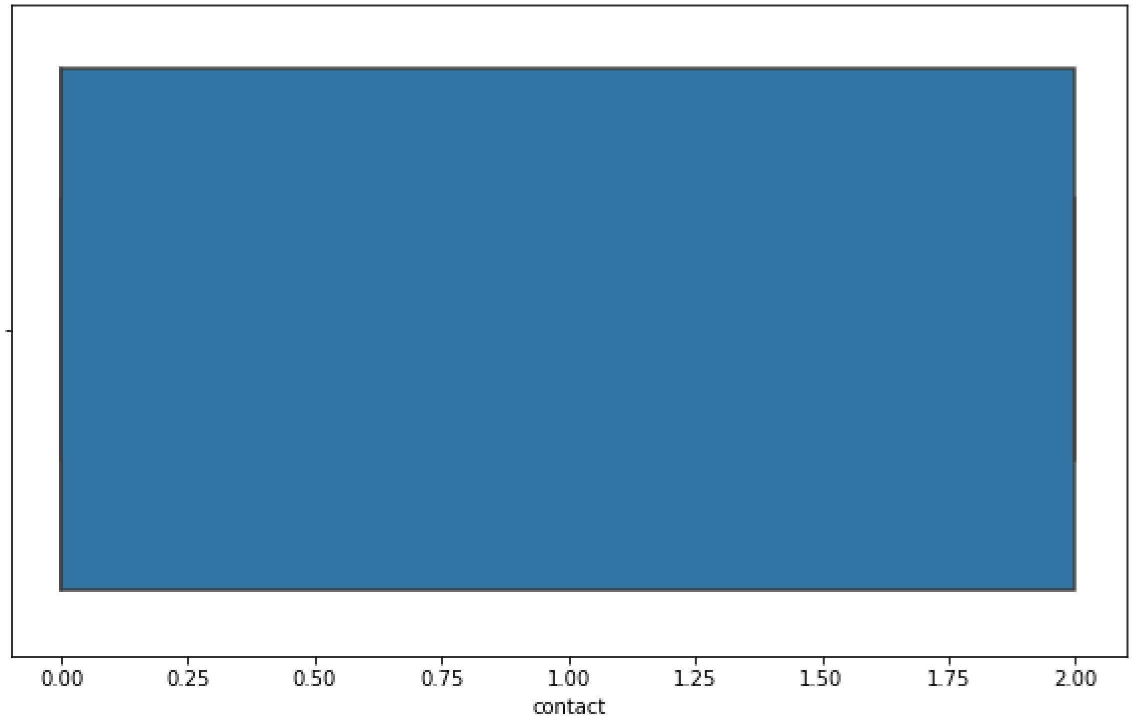
0.0
0.2
0.4
0.6
0.8
1.0
default



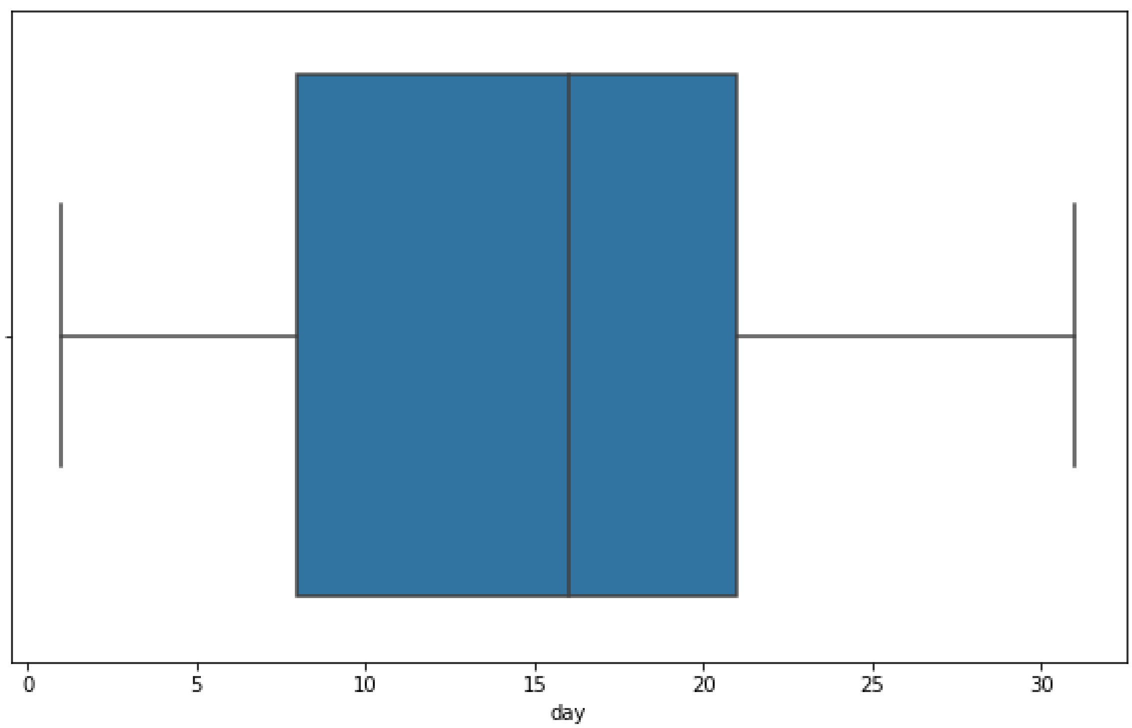
0
20000
40000
60000
80000
100000
balance


0.0
0.2
0.4
0.6
0.8
1.0
housing

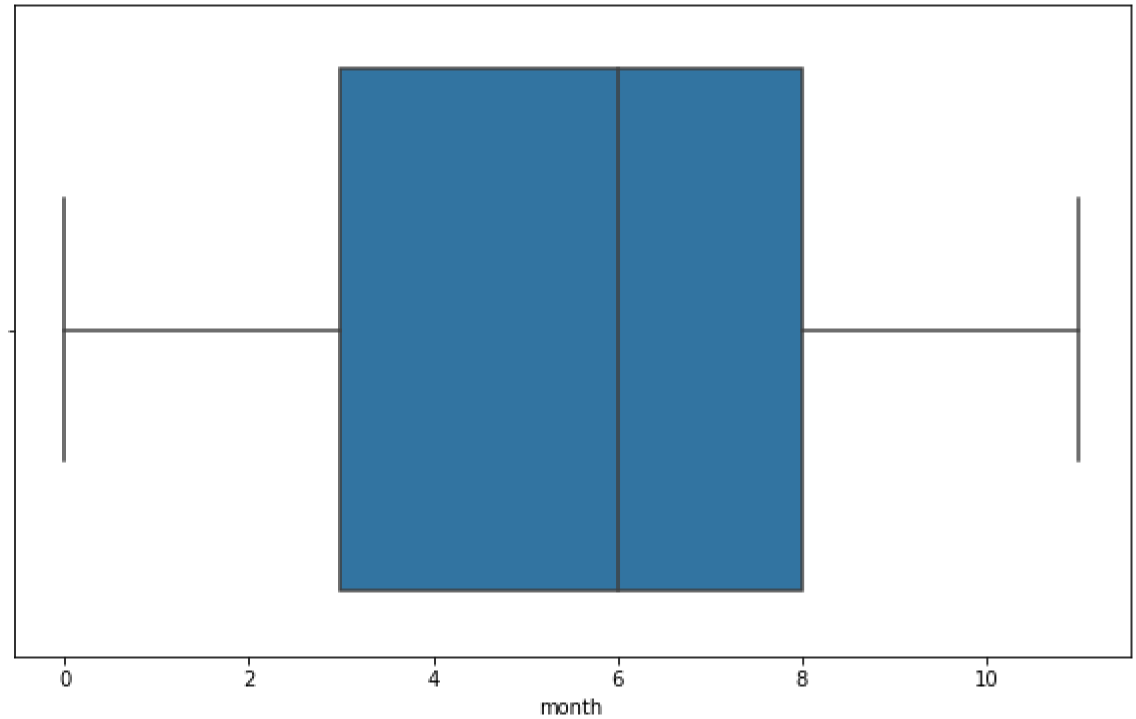

0.0
0.2
0.4
0.6
0.8
1.0
loan

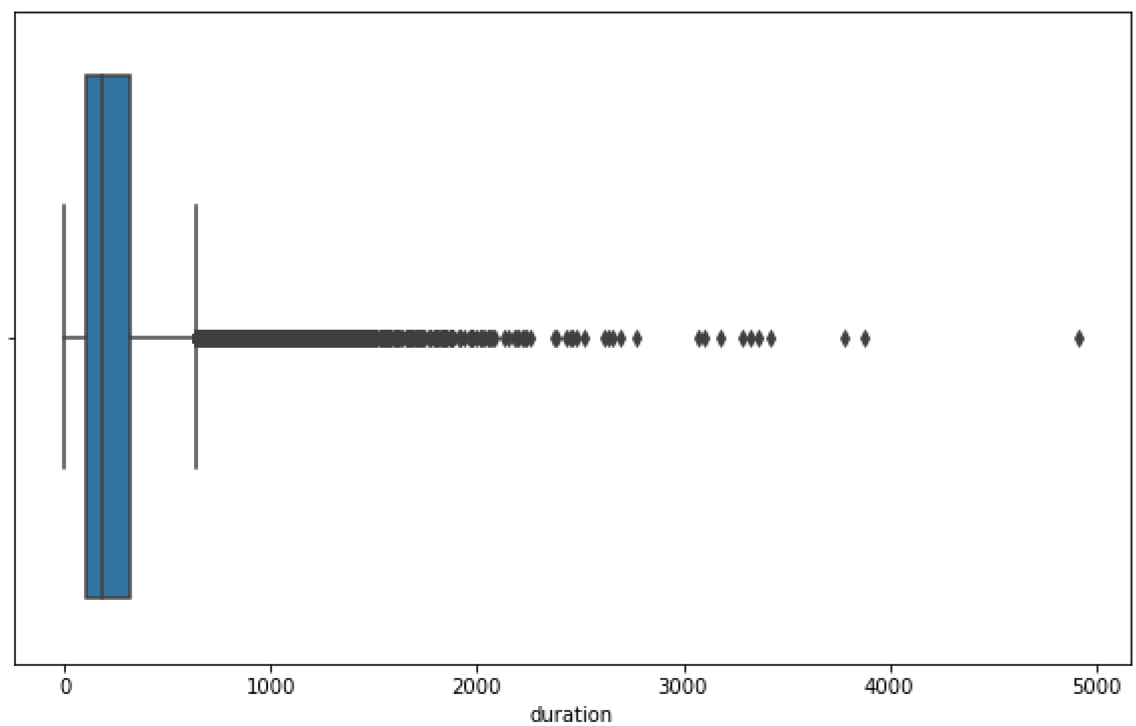


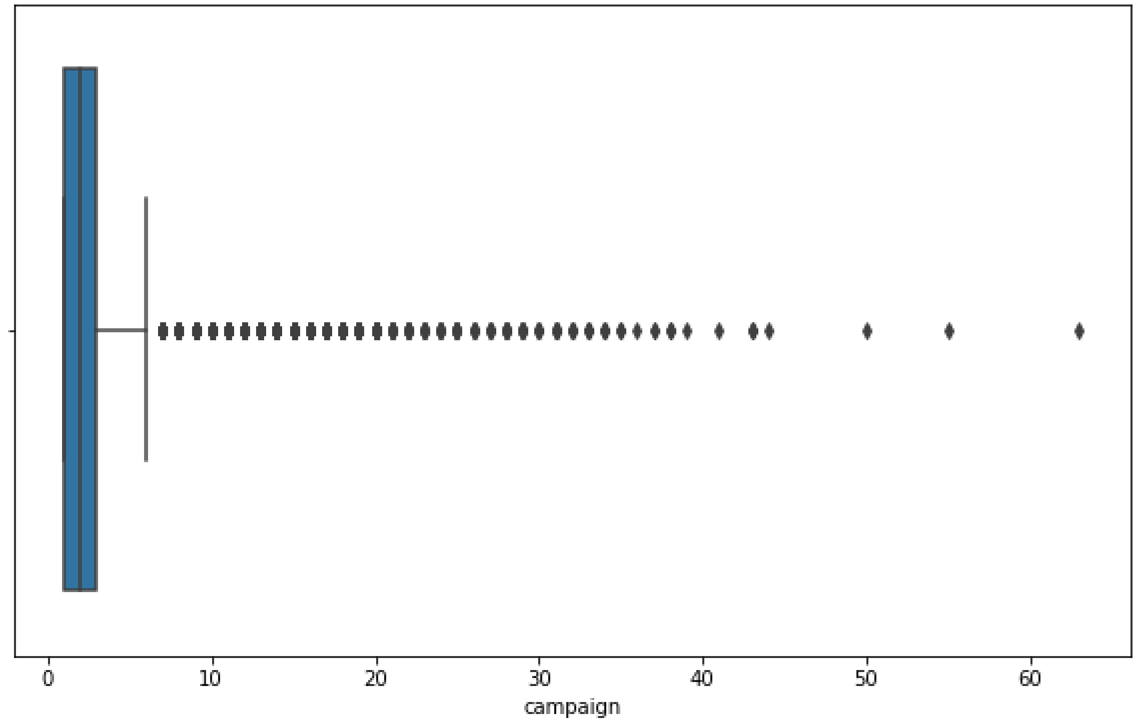
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
contact

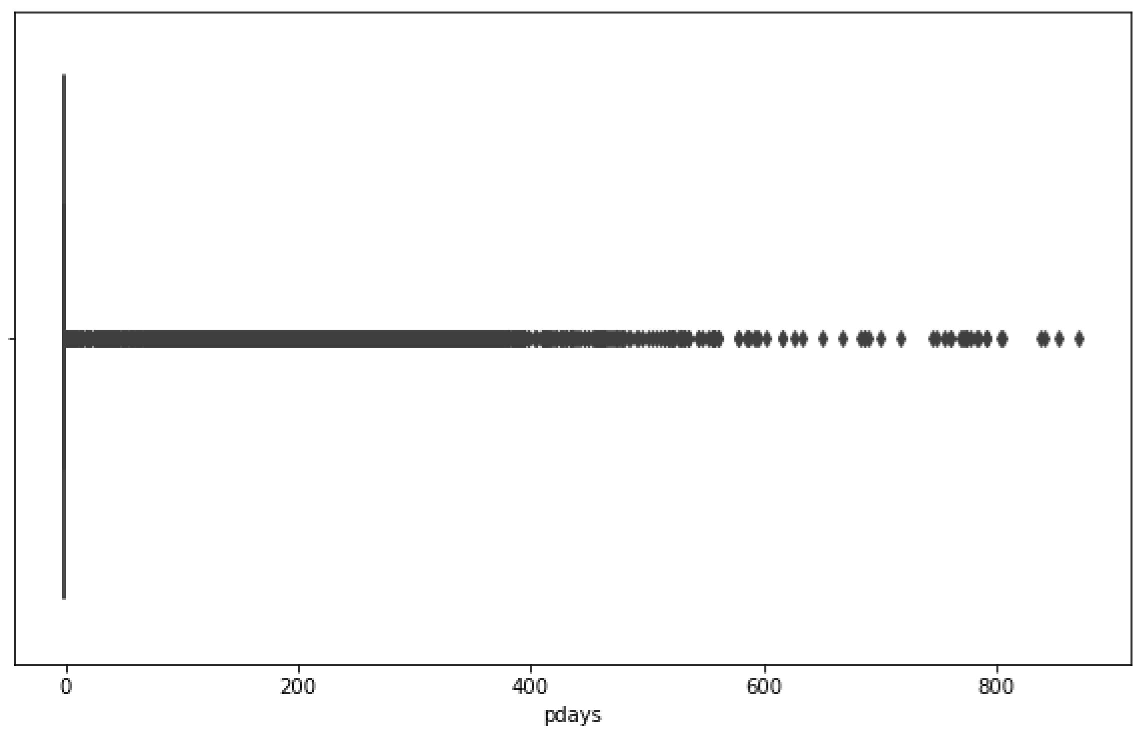


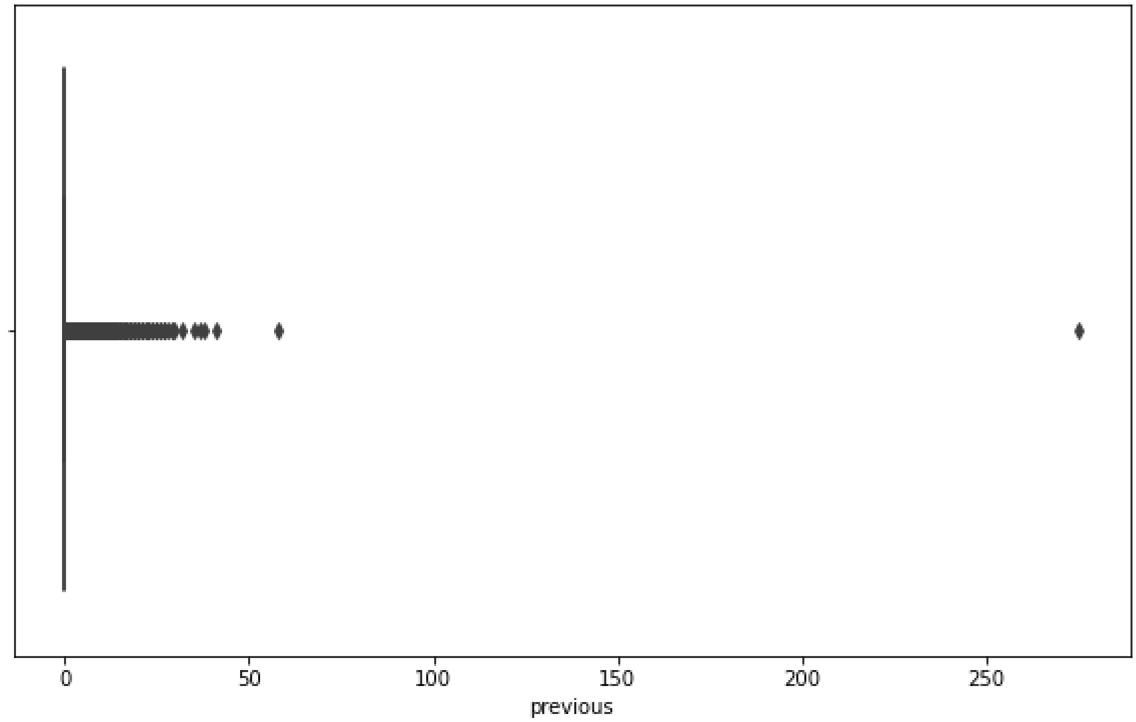
0
5
10
15
20
25
30
day

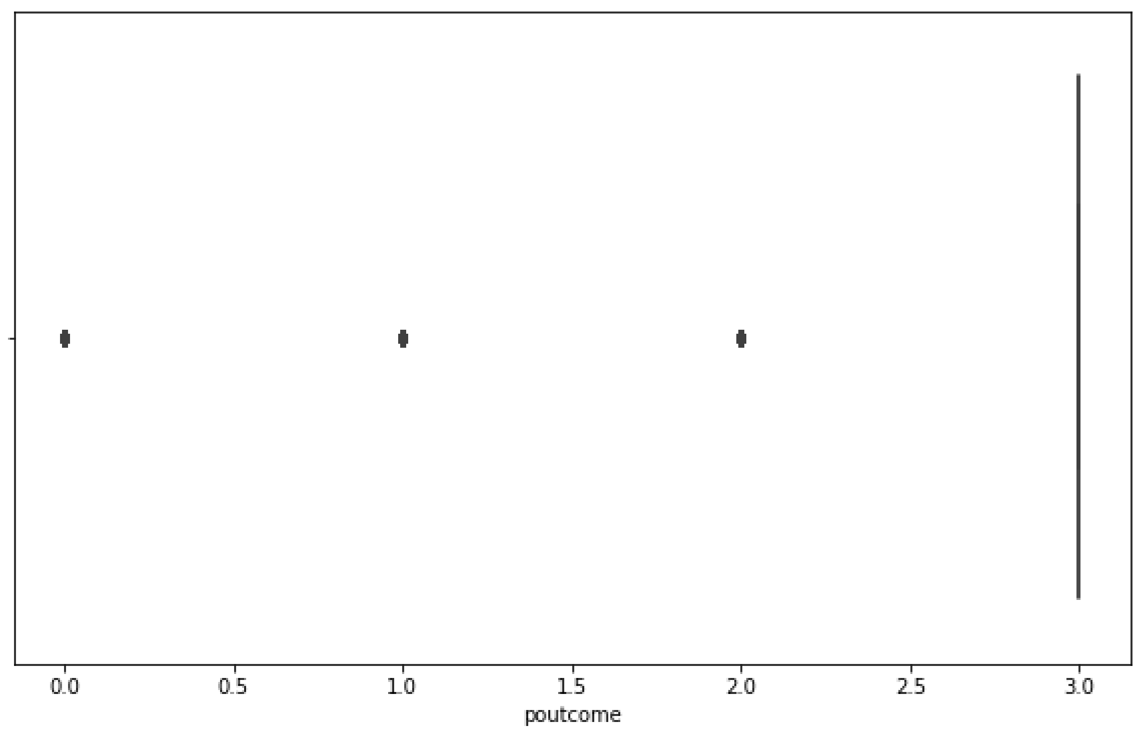

0
2
4
6
8
10
month


0
1000
2000
3000
4000
5000
duration


0
10
20
30
40
50
60
campaign


0
200
400
600
800
pdays





In [57]:
```
from scipy.stats import zscore
z=np.abs(zscore(x))
z.shape
```
Out[57]:
```
(31647, 16)
```

In [58]:
```
np.where(z>3)
```
Out[58]:
```
(array([   10,    21,    26, ..., 31622, 31645, 31646], dtype=int64),
 array([ 4, 12,  5, ..., 13, 14, 11], dtype=int64))
```

In [59]:
```
nd=train[(z<=3).all(axis=1)]
print(train.shape,'\n',nd.shape)
```
```
(31647, 17)
 (27584, 17)
```

In [60]:
```
(31647-27584)/31647*100
```

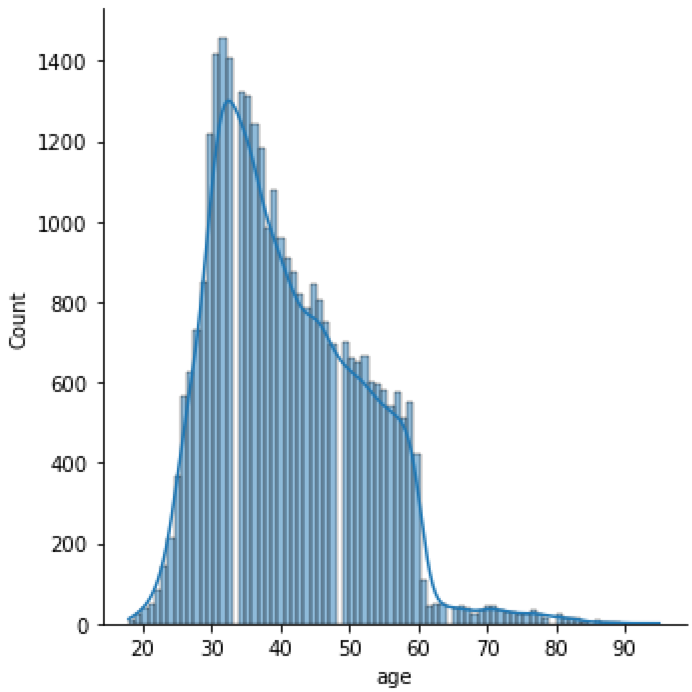
Out[60]:
```
12.83849969981357
```

Data loss of 13% is not acceptable. Hence we will not remove outliers. Also most of the columns are categorical column for which we dont need to remove outlier.

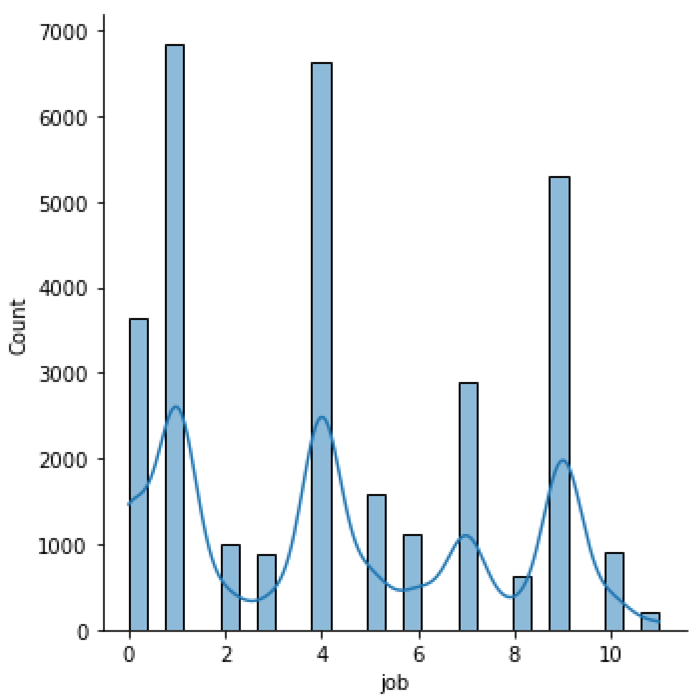
Skewness

In [61]:
```
for i in x:
    plt.figure(figsize=(20,8))
    sns.displot(x[i], kde=True)
```

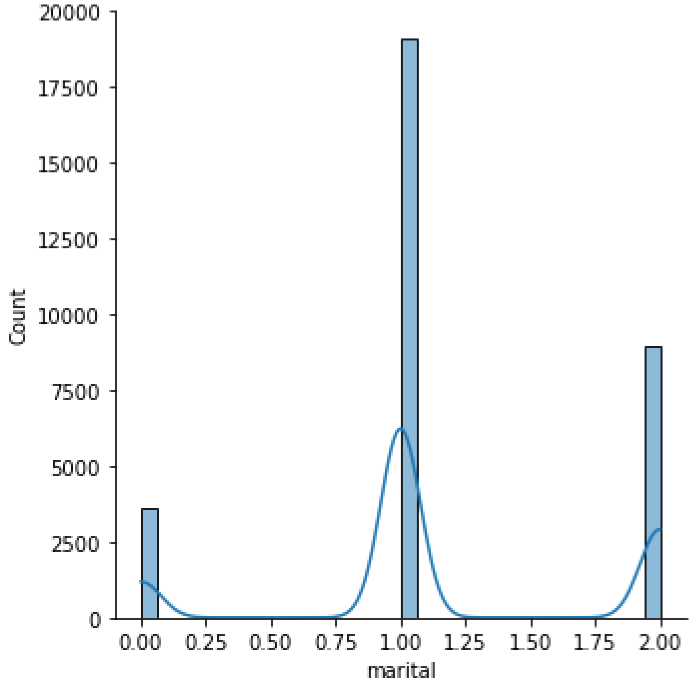
```
<Figure size 1440x576 with 0 Axes>
```



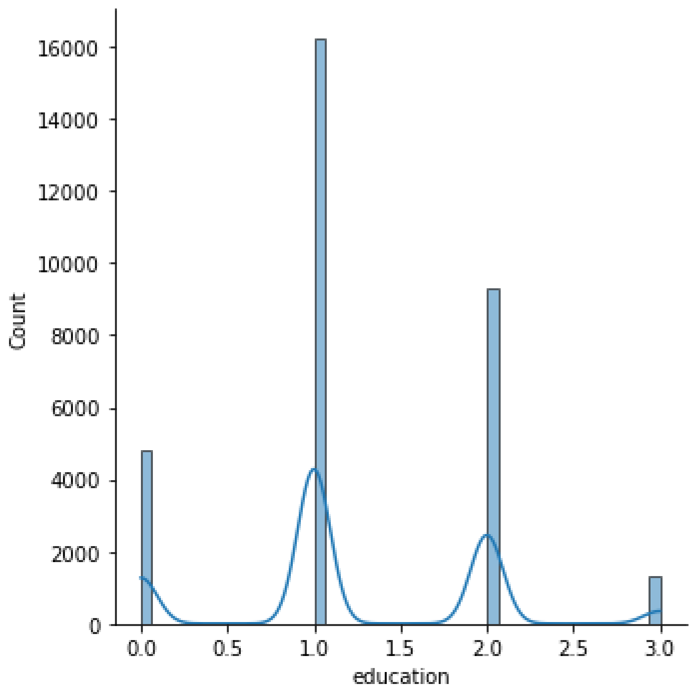

```
<Figure size 1440x576 with 0 Axes>
```



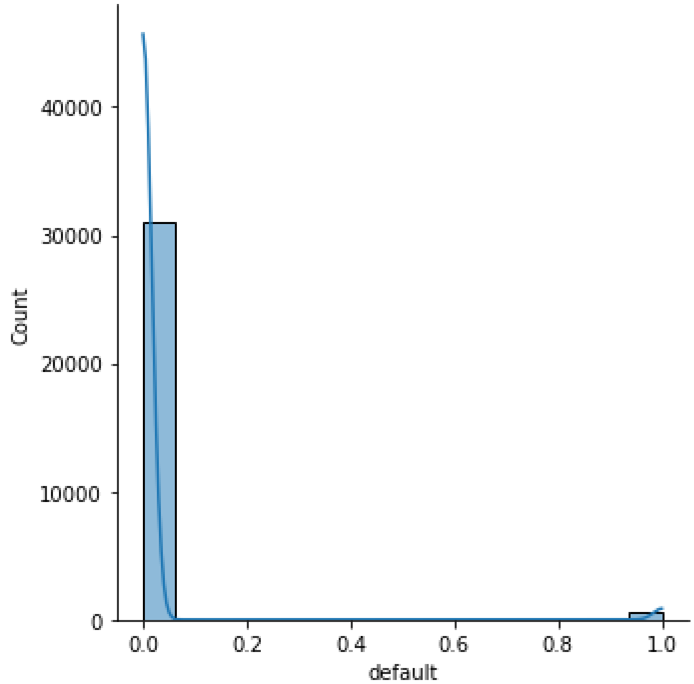

```
<Figure size 1440x576 with 0 Axes>
```



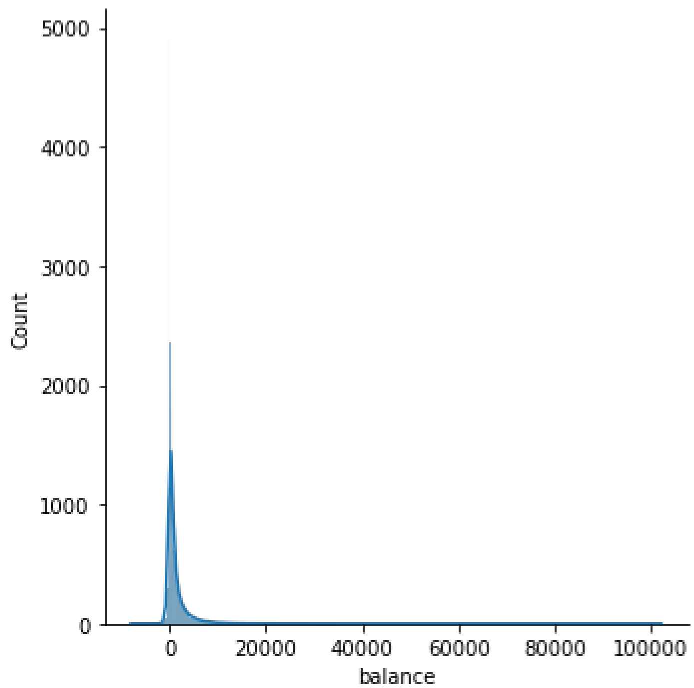
<Figure size 1440x576 with 0 Axes>



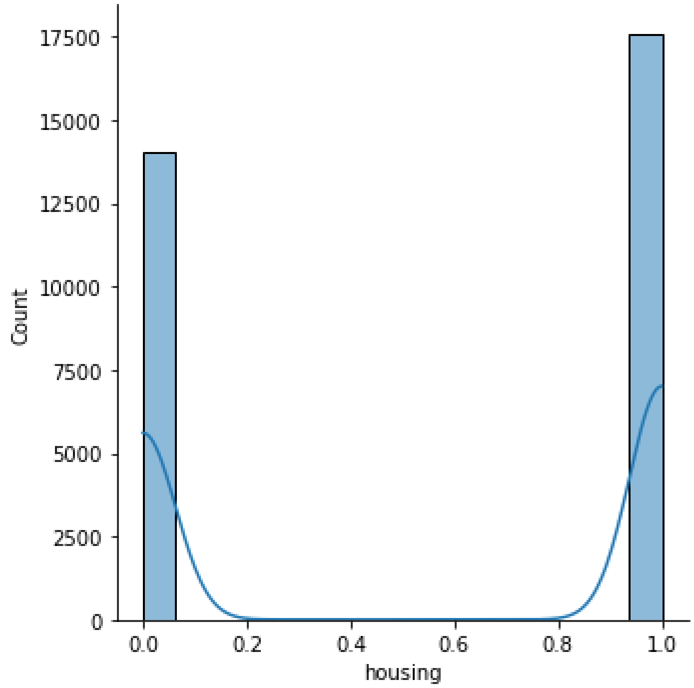
<Figure size 1440x576 with 0 Axes>



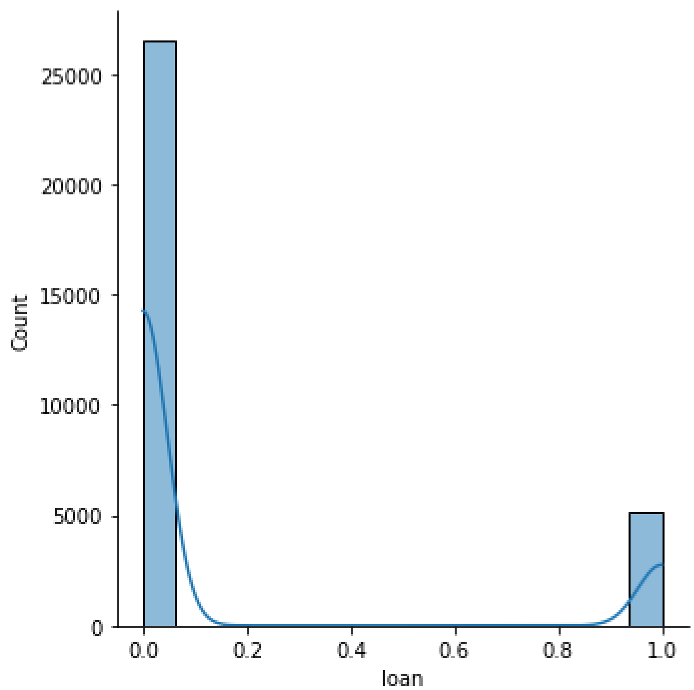
<Figure size 1440x576 with 0 Axes>



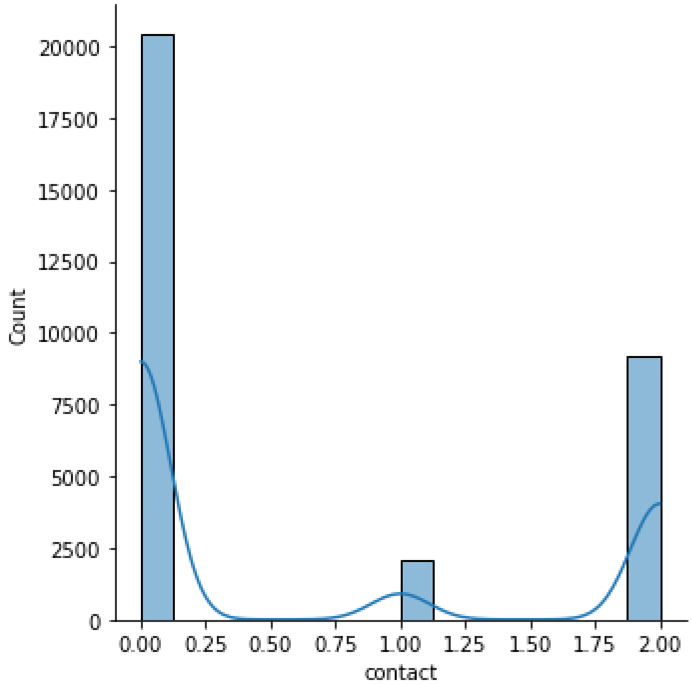
<Figure size 1440x576 with 0 Axes>



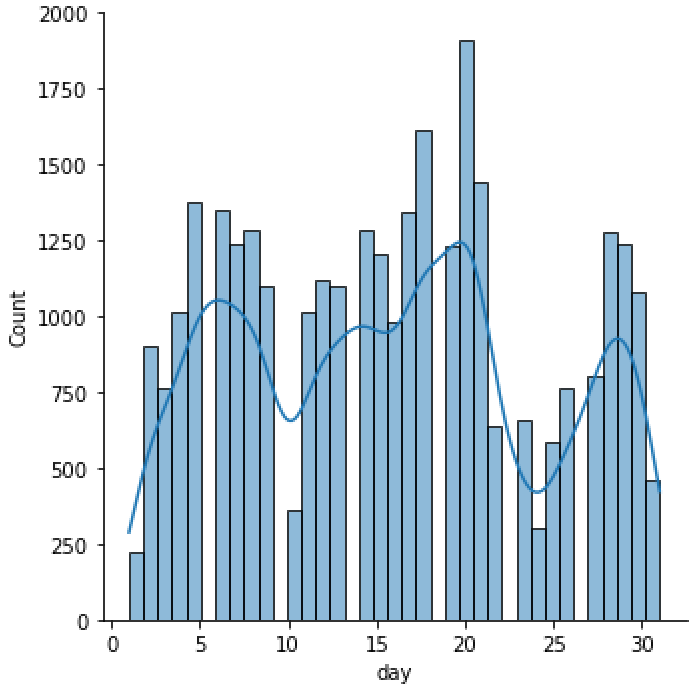
<Figure size 1440x576 with 0 Axes>



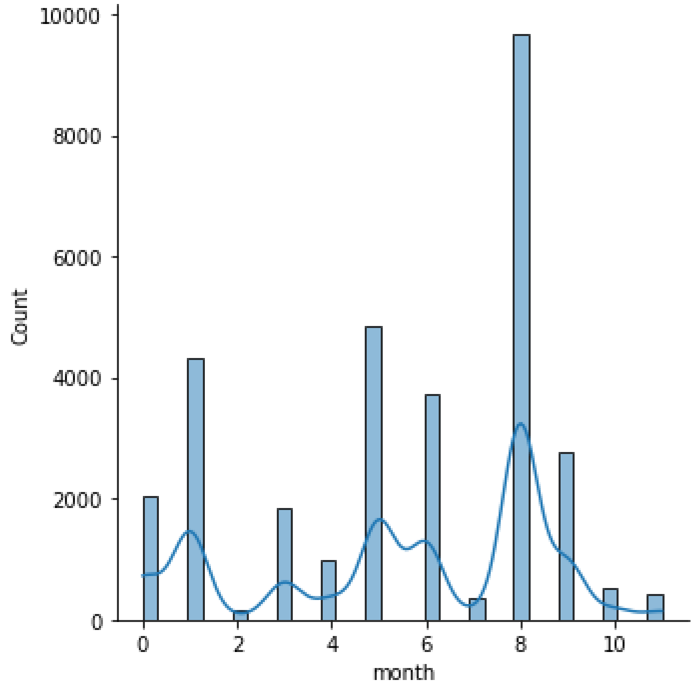
<Figure size 1440x576 with 0 Axes>



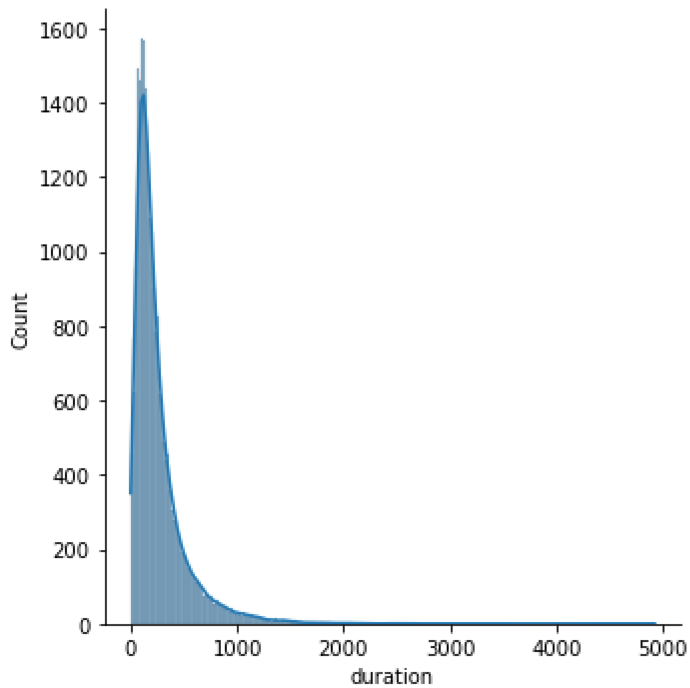
<Figure size 1440x576 with 0 Axes>



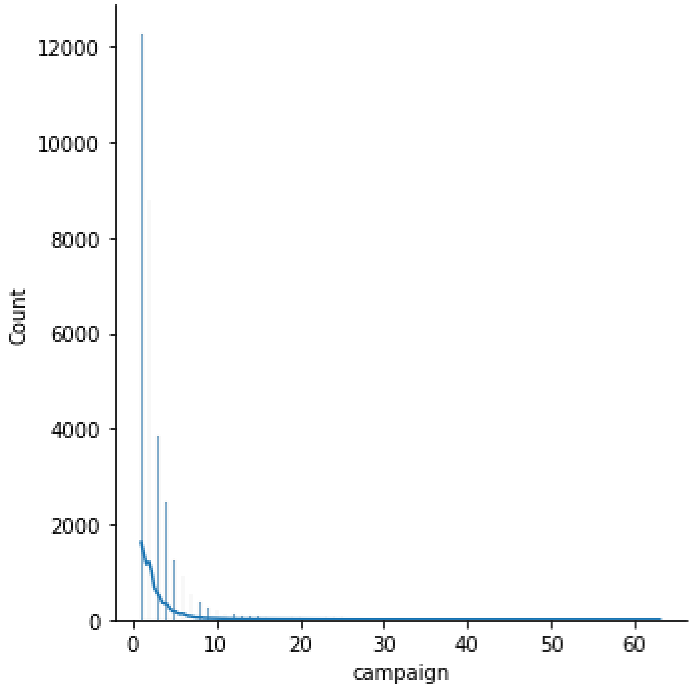
<Figure size 1440x576 with 0 Axes>



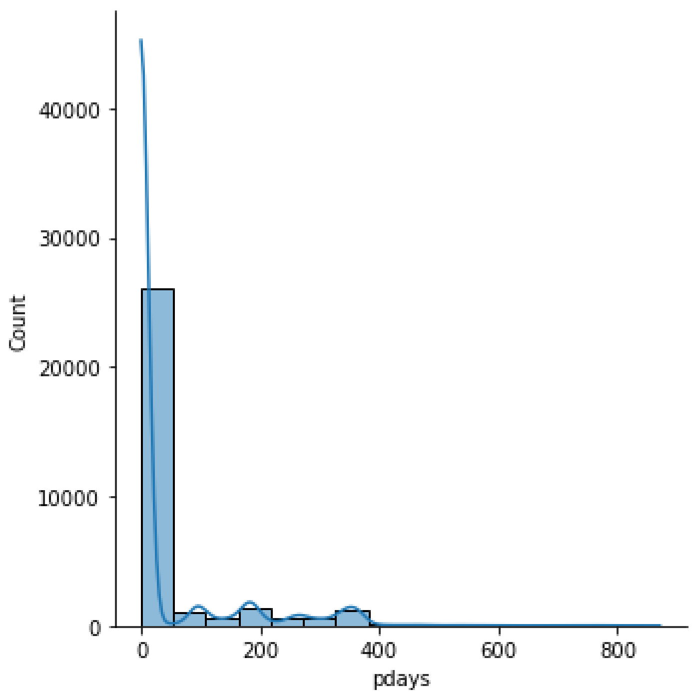
<Figure size 1440x576 with 0 Axes>



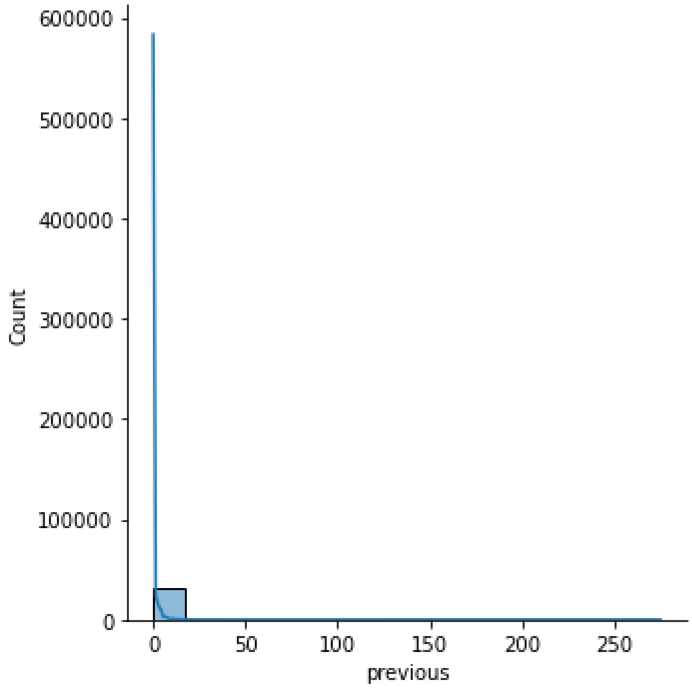
<Figure size 1440x576 with 0 Axes>



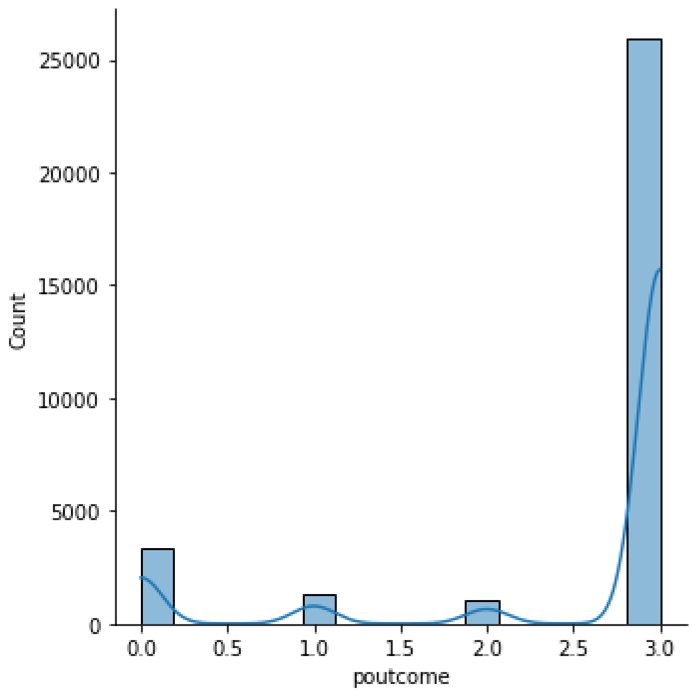
<Figure size 1440x576 with 0 Axes>



<Figure size 1440x576 with 0 Axes>



<Figure size 1440x576 with 0 Axes>



Data is skewed. So we need to remove skewness.

In [62]:
```
x.skew()
```

Out[62]:
```
age           0.681607
job           0.264817
marital      -0.100071
education     0.199441
default       7.149903
balance       7.995696
housing      -0.223918
loan          1.833474
contact       0.758602
day           0.087185
month        -0.486498
duration      3.199766
campaign      4.873935
pdays         2.642374
previous     49.302348
```

```
poutcome      -1.996421
dtype: float64
```

In [63]:
```python
test.skew()
```

Out[63]:
```
age           0.692404
job           0.254647
marital      -0.109220
education     0.192137
default       7.483552
balance       9.165015
housing      -0.226771
loan          1.898587
contact       0.794849
day           0.106806
month        -0.465848
duration      3.017221
campaign      4.958236
pdays         2.555601
previous      8.704583
poutcome     -1.921847
dtype: float64
```

Column 'previuos' has very high skewness for both test and train set.

Removing skewness

In [64]:
```python
from sklearn.preprocessing import PowerTransformer

pt=PowerTransformer()

# removing skewness in train data
xs=pt.fit_transform(x)
x=pd.DataFrame(xs,columns=x.columns)

# removing skewness in train data
ts=pt.fit_transform(test)
test=pd.DataFrame(ts,columns=test.columns)
```

In [65]:
```python
x.skew()
```

Out[65]:
```
age           0.008940
job          -0.145894
marital      -0.050323
education    -0.039618
default       7.149903
balance       0.821075
housing      -0.223918
loan          1.833474
contact       0.627828
day          -0.159858
month        -0.383709
duration      0.017331
campaign      0.230683
pdays         1.660825
previous      1.661485
poutcome     -1.698601
dtype: float64
```

In [66]:
```python
test.skew()
```

Out[66]:
```
age           0.007857
job          -0.148339
marital      -0.054738
```

```
education    -0.039290
default       7.483552
balance       2.258038
housing      -0.226771
loan          1.898587
contact       0.662690
day          -0.153240
month        -0.378233
duration      0.019436
campaign      0.231562
pdays         1.609653
previous      1.610955
poutcome     -1.648855
dtype: float64
```

Correlation

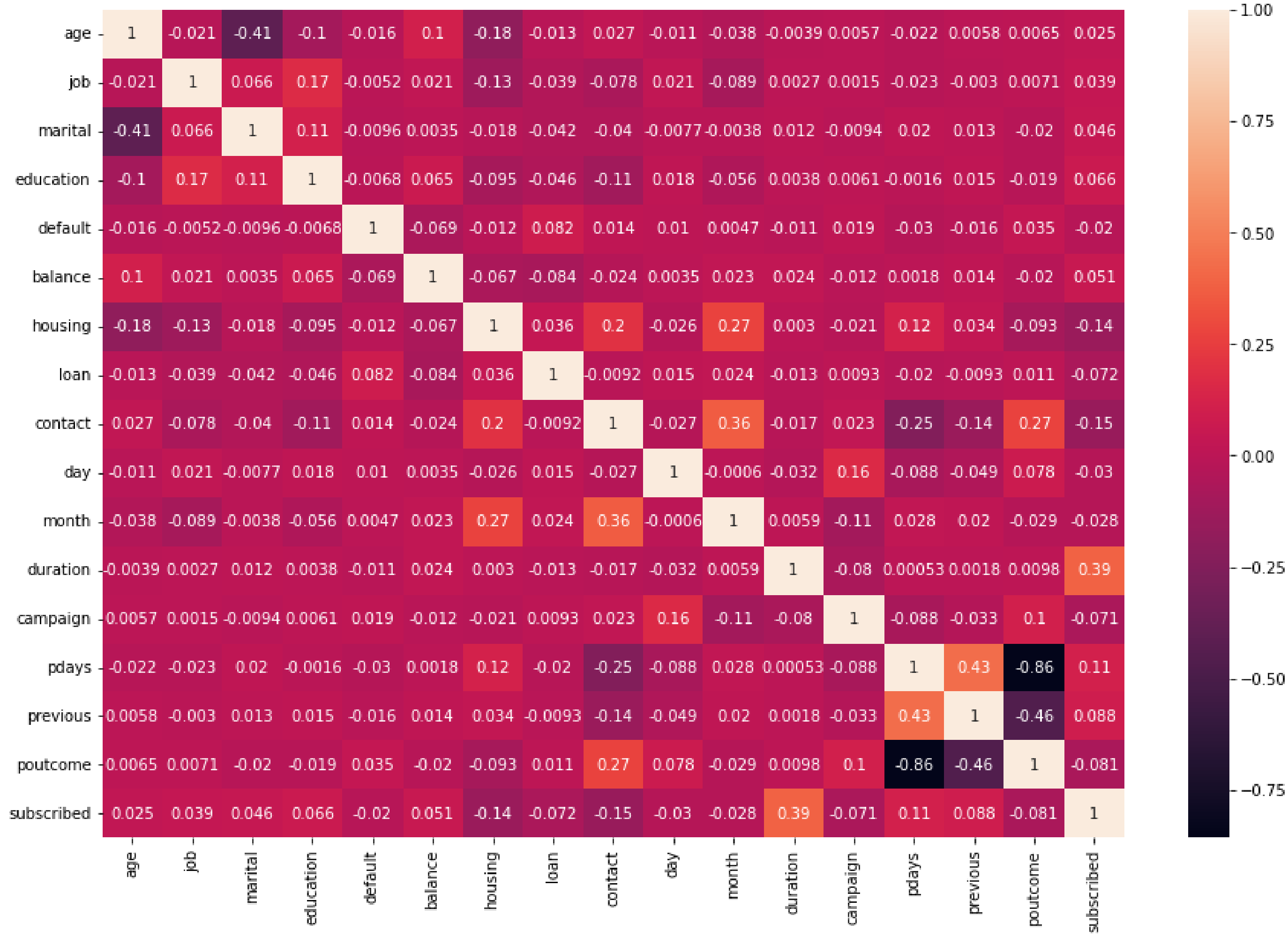
Checking correlation of feature columns with target, if any column has very weak correlation we can remove that column.

In [67]:
```python
train.corr()['subscribed']
```

Out[67]:
```
age            0.024538
job            0.038921
marital        0.046043
education      0.066051
default       -0.020168
balance        0.050807
housing       -0.141092
loan          -0.072266
contact       -0.150051
day           -0.029600
month         -0.028088
duration       0.389838
campaign      -0.070607
pdays          0.108290
previous       0.088081
poutcome      -0.080895
subscribed     1.000000
Name: subscribed, dtype: float64
```

In [68]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(train.corr(), annot=True)
```

Out[68]:
```
<AxesSubplot:>
```



In [69]:
```
#### every feature column has weak corelation with target, so we will not remove any col
```

Resampling

In [70]:
```
train['subscribed'].value_counts(normalize=True)*100
```

Out[70]:
```
0    88.261131
1    11.738869
Name: subscribed, dtype: float64
```

In [71]:
```
train['subscribed'].value_counts()
```

Out[71]:
```
0    27932
1     3715
Name: subscribed, dtype: int64
```

There is data inbalanced and data is small. Hence we will use oversapling.

Handling Data inbalance

In [72]:
```
#oversampling
from imblearn.over_sampling import SMOTE
smt=SMOTE()
x,y=smt.fit_resample(x,y)
```

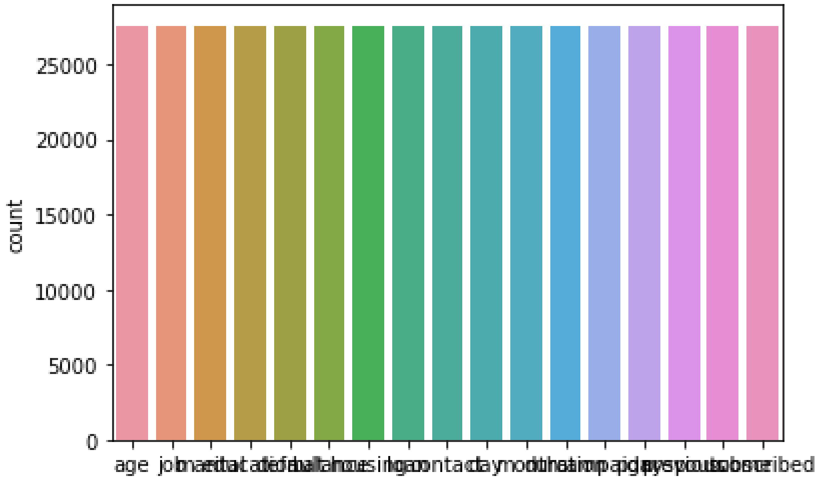
In [75]:
```
y.value_counts()
```

Out[75]:
```
0    27932
1    27932
```

```
Name: subscribed, dtype: int64
```

In [76]:
```
sns.countplot(data=nd)
```

Out[76]:
```
<AxesSubplot:ylabel='count'>
```



Scaling

In [77]:
```
# scaling the data
from sklearn.preprocessing import MinMaxScaler, StandardScaler

scaler=StandardScaler()

# scaling train data
xd=scaler.fit_transform(x)
x=pd.DataFrame(xd,columns=x.columns)

# scaling test data
td=scaler.fit_transform(test)
test=pd.DataFrame(td,columns=test.columns)
```

In [78]:
```
x
```

Out[78]:

	age	job	marital	education	default	balance	housing	loan	contact	day
0	1.260512	-1.708803	-0.348434	2.190069	-0.122506	0.291876	-0.949441	-0.386216	1.337596	0.485119
1	-0.900617	1.650129	-0.348434	-0.343298	-0.122506	-0.527549	-0.949441	-0.386216	-0.609938	0.596153
2	-1.436063	0.833109	-0.348434	-0.343298	-0.122506	-0.102197	1.058967	-0.386216	-0.609938	0.372379
3	1.321919	0.047375	-1.942426	0.982014	-0.122506	0.755166	-0.949441	-0.386216	-0.609938	0.813519
4	-0.900617	1.265180	-0.348434	-0.343298	-0.122506	-0.452494	1.058967	-0.386216	-0.609938	-1.505248
...	...	...	...	...	...	...	...	...	...	...
55859	-1.041725	1.249286	1.303171	-0.343298	-0.122506	-0.096463	-0.949441	-0.386216	-0.609938	-1.865056
55860	-1.255550	-0.355517	-0.348434	0.677969	-0.122506	-0.356342	1.058967	2.595892	1.734094	-1.065565
55861	-0.744238	-1.096891	-0.348434	-0.343298	-0.122506	-0.459878	1.058967	-0.386216	-0.609938	0.151175
55862	-1.479259	0.898058	1.303171	-0.343298	-0.122506	0.145048	1.058967	-0.386216	-0.609938	0.189307
55863	0.408987	1.092895	-0.984026	-0.953126	-0.122506	-0.107481	1.058967	-0.386216	-0.609938	1.037291

55864 rows × 16 columns

In [79]:
```
test
```

Out[79]:

	age	job	marital	education	default	balance	housing	loan	contact	day
0	-0.830543	0.852310	-0.287967	-0.256082	-0.131336	-0.349877	0.893033	-0.429564	-0.726140	-0.001693
1	2.549644	0.365121	-1.884603	-1.737907	-0.131336	0.636076	-1.119779	-0.429564	1.085204	-2.093781
2	-0.959923	0.618588	1.372809	1.033920	-0.131336	-0.335968	0.893033	-0.429564	1.431917	0.115298
3	1.414890	0.852310	1.372809	-1.737907	-0.131336	0.940270	0.893033	-0.429564	1.085204	-0.242825
4	0.520126	-1.023489	-1.884603	-0.256082	-0.131336	-2.747632	-1.119779	2.327941	1.431917	-1.691501
...	...	...	...	...	...	...	...	...	...	...
13559	-0.038159	0.086458	-0.287967	1.033920	-0.131336	-0.392516	-1.119779	-0.429564	-0.726140	1.386449
13560	1.213253	-1.023489	-0.287967	-1.737907	-0.131336	0.473571	0.893033	-0.429564	1.431917	0.563344
13561	-0.468654	0.365121	-0.287967	-1.737907	-0.131336	-0.266423	0.893033	-0.429564	-0.726140	1.483967
13562	-1.233677	-1.613572	1.372809	-0.256082	-0.131336	-0.186352	-1.119779	-0.429564	-0.726140	-0.760845
13563	-1.233677	-1.613572	-0.287967	-0.256082	-0.131336	-0.424459	0.893033	-0.429564	-0.726140	-1.193781

13564 rows × 16 columns

ML Modeling

In [85]:
```
# Getting the best random stae value
from sklearn.linear_model import LogisticRegression
logr= LogisticRegression()
for i in range(0,100):
    x_train,x_test,y_train,y_test=train_test_split(x,y, test_size=0.2, random_state=i)
    logr.fit(x_train,y_train)
    pred_train=logr.predict(x_train)
    pred_test=logr.predict(x_test)
    if (accuracy_score(y_train,pred_train)*100>82.3 and accuracy_score(y_test,pred_test)
                  print("At random state", i ,"the training accuracy is", accuracy_s
                  print("At random state", i ,"the test accuracy is", accuracy_score
                  print("\n")
```

```
At random state 3 the training accuracy is 0.8239242800563872
At random state 3 the test accuracy is 0.8233240848473999


At random state 5 the training accuracy is 0.8230516211317715
At random state 5 the test accuracy is 0.8260986306274054


At random state 8 the training accuracy is 0.8230068693920476
At random state 8 the test accuracy is 0.8285151705003132


At random state 11 the training accuracy is 0.8238124007070775
At random state 11 the test accuracy is 0.8235030878009487


At random state 14 the training accuracy is 0.8233201315701147
At random state 14 the test accuracy is 0.8261881321041797


At random state 16 the training accuracy is 0.8240809111454208
```

```
At random state 16 the test accuracy is 0.8231450818938513


At random state 19 the training accuracy is 0.82361101787832
At random state 19 the test accuracy is 0.8259196276738566


At random state 25 the training accuracy is 0.8238124007070775
At random state 25 the test accuracy is 0.8239505951848205


At random state 26 the training accuracy is 0.8233872591797006
At random state 26 the test accuracy is 0.826993645395149


At random state 29 the training accuracy is 0.8230516211317715
At random state 29 the test accuracy is 0.826725140964826


At random state 32 the training accuracy is 0.82361101787832
At random state 32 the test accuracy is 0.8235030878009487


At random state 37 the training accuracy is 0.8232977557002529
At random state 37 the test accuracy is 0.826009129150631


At random state 38 the training accuracy is 0.8235438902687342
At random state 38 the test accuracy is 0.8243086010919181


At random state 39 the training accuracy is 0.8233648833098387
At random state 39 the test accuracy is 0.8262776335809541


At random state 41 the training accuracy is 0.8230292452619096
At random state 41 the test accuracy is 0.8254721202899847


At random state 44 the training accuracy is 0.8234991385290104
At random state 44 the test accuracy is 0.8243981025686924


At random state 46 the training accuracy is 0.8235438902687342
At random state 46 the test accuracy is 0.8253826188132104


At random state 47 the training accuracy is 0.8231187487413574
At random state 47 the test accuracy is 0.8259196276738566


At random state 49 the training accuracy is 0.82361101787832
At random state 49 the test accuracy is 0.8244876040454667


At random state 50 the training accuracy is 0.8230963728714954
At random state 50 the test accuracy is 0.8259196276738566


At random state 54 the training accuracy is 0.8237676489673537
At random state 54 the test accuracy is 0.8252036158596617


At random state 55 the training accuracy is 0.8237452730974917
At random state 55 the test accuracy is 0.8248456099525642
```

```
At random state 56 the training accuracy is 0.8234991385290104
At random state 56 the test accuracy is 0.8243086010919181


At random state 57 the training accuracy is 0.8234543867892864
At random state 57 the test accuracy is 0.8243981025686924


At random state 58 the training accuracy is 0.8231411246112192
At random state 58 the test accuracy is 0.8258301261970823


At random state 59 the training accuracy is 0.8231635004810812
At random state 59 the test accuracy is 0.8263671350577284


At random state 61 the training accuracy is 0.8231858763509431
At random state 61 the test accuracy is 0.8268146424416003


At random state 65 the training accuracy is 0.8234991385290104
At random state 65 the test accuracy is 0.8246666069990155


At random state 72 the training accuracy is 0.8238571524468014
At random state 72 the test accuracy is 0.8249351114293386


At random state 73 the training accuracy is 0.8237900248372155
At random state 73 the test accuracy is 0.8241295981383693


At random state 74 the training accuracy is 0.8232977557002529
At random state 74 the test accuracy is 0.825024612906113


At random state 75 the training accuracy is 0.8231635004810812
At random state 75 the test accuracy is 0.8259196276738566


At random state 77 the training accuracy is 0.8243270457139021
At random state 77 the test accuracy is 0.8237715922312718


At random state 80 the training accuracy is 0.8234320109194245
At random state 80 the test accuracy is 0.8236820907544975


At random state 84 the training accuracy is 0.8236781454879059
At random state 84 the test accuracy is 0.8235030878009487


At random state 95 the training accuracy is 0.8233201315701147
At random state 95 the test accuracy is 0.8266356394880515


At random state 96 the training accuracy is 0.8237228972276297
At random state 96 the test accuracy is 0.8246666069990155


At random state 97 the training accuracy is 0.8238347765769394
At random state 97 the test accuracy is 0.8253826188132104


At random state 98 the training accuracy is 0.8238795283166633
```

```
At random state 98 the test accuracy is 0.8230555804170768
```

At randm state 25 we are receiving best accuracy of the model. Hence we will use random state=25 for our model.

LogisticRegression

In [95]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y, test_size=0.2, random_state=25)

logr.fit(x_train,y_train)
pred_test=logr.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test))
print('classification Report\n',classification_report(y_test,pred_test))
```

```
Accuracy
 0.8239505951848205
Confusion matrix
 [[4594 1066]
 [ 901 4612]]
classification Report
               precision    recall  f1-score   support

           0       0.84      0.81      0.82      5660
           1       0.81      0.84      0.82      5513

    accuracy                           0.82     11173
   macro avg       0.82      0.82      0.82     11173
weighted avg       0.82      0.82      0.82     11173
```

In [105…

```
#  Chosing best cross fold value
for j in range(2,10):
    cv_score=cross_val_score(logr,x,y,cv=j)
    cv_mean=cv_score.mean()
    print(f"AT cross fold {j} the cv score is {cv_mean}")
    print('\n')
```

```
AT cross fold 2 the cv score is 0.8234999283975368


AT cross fold 3 the cv score is 0.8233926498763576


AT cross fold 4 the cv score is 0.8234641271659745


AT cross fold 5 the cv score is 0.8235894969424175


AT cross fold 6 the cv score is 0.8235538214177757


AT cross fold 7 the cv score is 0.8237507869230958


AT cross fold 8 the cv score is 0.8235357296290993


AT cross fold 9 the cv score is 0.8236972259177505
```

At cv=7 we are getting cross value score nearest to our accuracy score.

In [97]:
```
# cross validation for logr model
cv_score=cross_val_score(logr,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.8237507869230958
Difference between accuracy and validation score 0.000199808261724721
```

Predicting output for test data we have.

In [98]:
```
# predicting for test set we are given
prediction_logr=logr.predict(test)
```

In [99]:
```
prediction_logr
```

Out[99]:
```
array([0, 1, 1, ..., 0, 1, 1], dtype=int64)
```

Ensemble

In [103…
```
from sklearn.ensemble import GradientBoostingClassifier, AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
```

GradientBoostingClassifier

In [106…
```
gb=GradientBoostingClassifier()

gb.fit(x_train,y_train)
pred_test_gb=gb.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test_gb))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_gb))
print('classification Report\n',classification_report(y_test,pred_test_gb))
```

```
Accuracy
 0.912646558668218
Confusion matrix
 [[5017  643]
 [ 333 5180]]
classification Report
               precision    recall  f1-score   support

           0       0.94      0.89      0.91      5660
           1       0.89      0.94      0.91      5513

    accuracy                           0.91     11173
   macro avg       0.91      0.91      0.91     11173
weighted avg       0.91      0.91      0.91     11173
```

In [107…
```
# cross validation for GradientBoostingClassifier model
cv_score=cross_val_score(gb,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.9054678936049917
Difference between accuracy and validation score 0.007178665063226286
```

In [119…
```python
# predicting for test set we are given
prediction_gb=gb.predict(test)
```

In [120…
```python
prediction_gb
```

Out[120]:
```
array([0, 1, 1, ..., 1, 1, 1], dtype=int64)
```

AdaBoostClassifier

In [111…
```python
ad=AdaBoostClassifier()

ad.fit(x_train,y_train)
pred_test_ad=ad.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test_ad))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_ad))
print('classification Report\n',classification_report(y_test,pred_test_ad))
```

```
Accuracy
 0.8774724782958919
Confusion matrix
 [[4921  739]
 [ 630 4883]]
classification Report
               precision    recall  f1-score   support

           0       0.89      0.87      0.88      5660
           1       0.87      0.89      0.88      5513

    accuracy                           0.88     11173
   macro avg       0.88      0.88      0.88     11173
weighted avg       0.88      0.88      0.88     11173
```

In [112…
```python
# cross validation for AdaBoostClassifier model
cv_score=cross_val_score(ad,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.8746965212268144
Difference between accuracy and validation score 0.002775957069077517
```

In [117…
```python
# predicting for test set we are given
prediction_ad=ad.predict(test)
```

In [118…
```python
prediction_ad
```

Out[118]:
```
array([0, 1, 1, ..., 1, 1, 1], dtype=int64)
```

RandomForestClassifier

In [115…
```python
rfc=RandomForestClassifier()

rfc.fit(x_train,y_train)
pred_test_rfc=rfc.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test_rfc))
```

```
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_rfc))
print('classification Report\n',classification_report(y_test,pred_test_rfc))
```

```
Accuracy
 0.9445090843998926
Confusion matrix
 [[5234  426]
 [ 194 5319]]
classification Report
               precision    recall  f1-score   support

           0       0.96      0.92      0.94      5660
           1       0.93      0.96      0.94      5513

    accuracy                           0.94     11173
   macro avg       0.95      0.94      0.94     11173
weighted avg       0.95      0.94      0.94     11173
```

In [116…

```
# cross validation for RandomForestClassifier model
cv_score=cross_val_score(rfc,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.9429693207547661
Difference between accuracy and validation score 0.001539763645126424
```

In [121…

```
# predicting for test set we are given
prediction_rfc=rfc.predict(test)
```

In [122…

```
prediction_rfc
```

Out[122]:

```
array([0, 1, 1, ..., 1, 1, 1], dtype=int64)
```

ExtraTreesClassifier

In [123…

```
etc=ExtraTreesClassifier()

etc.fit(x_train,y_train)
pred_test_etc=etc.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test_etc))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_etc))
print('classification Report\n',classification_report(y_test,pred_test_etc))
```

```
Accuracy
 0.9621408753244428
Confusion matrix
 [[5315  345]
 [  78 5435]]
classification Report
               precision    recall  f1-score   support

           0       0.99      0.94      0.96      5660
           1       0.94      0.99      0.96      5513

    accuracy                           0.96     11173
   macro avg       0.96      0.96      0.96     11173
weighted avg       0.96      0.96      0.96     11173
```

In [124…

```
# cross validation for ExtraTreesClassifier model
```

```
cv_score=cross_val_score(etc,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.9637334605958395
Difference between accuracy and validation score -0.0015925852713967181
```

In [127…

```
# predicting for test set we are given
prediction_etc=etc.predict(test)
```

In [128…

```
prediction_etc
```

Out[128]:

```
array([0, 1, 1, ..., 1, 1, 1], dtype=int64)
```

DecisionTreeClassifier

In [126…

```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier()

dtc.fit(x_train,y_train)
pred_test_dtc=dtc.predict(x_test)

print('Accuracy\n', accuracy_score(y_test,pred_test_dtc))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_dtc))
print('classification Report\n',classification_report(y_test,pred_test_dtc))
```

```
Accuracy
 0.9001163519198067
Confusion matrix
 [[5056  604]
 [ 512 5001]]
classification Report
               precision    recall  f1-score   support

           0       0.91      0.89      0.90      5660
           1       0.89      0.91      0.90      5513

    accuracy                           0.90     11173
   macro avg       0.90      0.90      0.90     11173
weighted avg       0.90      0.90      0.90     11173
```

In [129…

```
# cross validation for DecisionTreeClassifier model
cv_score=cross_val_score(dtc,x,y,cv=7)
cv_mean=cv_score.mean()
print(f"cv score is {cv_mean}")
print('Difference between accuracy and validation score', accuracy_score(y_test,pred_tes
```

```
cv score is 0.9049488462416536
Difference between accuracy and validation score -0.0048324943218469585
```

In [130…

```
# predicting for test set we are given
prediction_dtc=dtc.predict(test)
```

In [131…

```
prediction_dtc
```

Out[131]:

```
array([0, 0, 1, ..., 1, 1, 1], dtype=int64)
```

Tuning

We will do hepertuning on our best model(ExtraTreesClassifier)

In [132…

```
from sklearn.model_selection import GridSearchCV

parameters={

    "max_depth":[3,5,8],
    "max_features":["auto", "sqrt", "log2"],
    "criterion":["gini", "entropy"],
    "n_estimators":[50,100,150]
    }
```

In [133…

```
clf=GridSearchCV(ExtraTreesClassifier(),parameters)
clf.fit(x_train, y_train)
print(clf.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 100}
```

In [134…

```
tuned_etc=ExtraTreesClassifier(n_estimators= 100, max_features='sqrt', max_depth= 8, cri
tuned_etc.fit(x_train, y_train)

pred_test_tuned=tuned_etc.predict(x_test)

print('Accuracy\n',accuracy_score(y_test,pred_test_tuned))
print('Confusion matrix\n',confusion_matrix(y_test,pred_test_tuned))
print('classification Report\n',classification_report(y_test,pred_test_tuned))
```

```
Accuracy
 0.8468629732390585
Confusion matrix
 [[4655 1005]
 [ 706 4807]]
classification Report
               precision    recall  f1-score   support

           0       0.87      0.82      0.84      5660
           1       0.83      0.87      0.85      5513

    accuracy                           0.85     11173
   macro avg       0.85      0.85      0.85     11173
weighted avg       0.85      0.85      0.85     11173
```

In [135…

```
# predicting for test set we are given
prediction_tuned_etc=tuned_etc.predict(test)
```

In [136…

```
prediction_tuned_etc
```

Out[136]:

```
array([0, 1, 1, ..., 0, 1, 1], dtype=int64)
```

AUC ROC curve

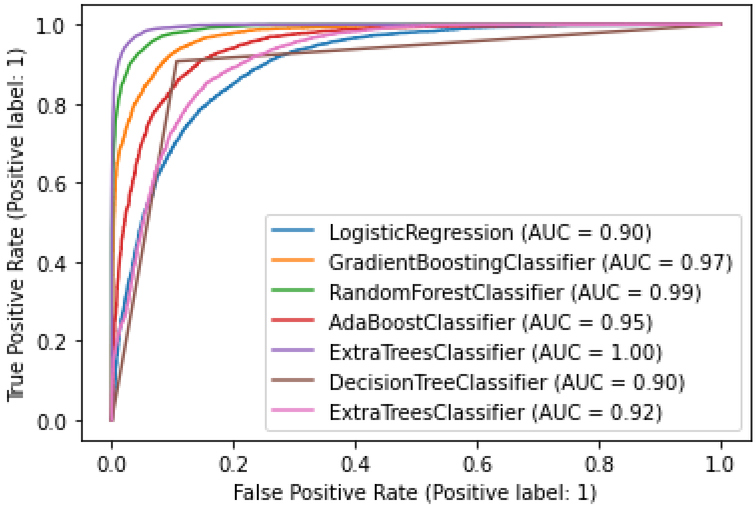
In [142…

```
from sklearn.metrics import plot_roc_curve

plt.figure(figsize=(20,10))
disp=plot_roc_curve(logr,x_test, y_test)
plot_roc_curve(gb,x_test, y_test,ax=disp.ax_)
plot_roc_curve(rfc,x_test, y_test,ax=disp.ax_)
plot_roc_curve(ad,x_test, y_test,ax=disp.ax_)
plot_roc_curve(etc,x_test, y_test,ax=disp.ax_)
plot_roc_curve(dtc,x_test, y_test,ax=disp.ax_)
```

```
plot_roc_curve(tuned_etc,x_test, y_test,ax=disp.ax_)
plt.legend(prop={'size':10},loc='lower right')
plt.show()
```

<Figure size 1440x720 with 0 Axes>



Model Saving

Since ExtraTreesClassifier is providing the best result(minimum difference between accuracy and validation score). So we will save the ExtraTreesClassifier model.

In [144…

```
import pickle
filename='term_deposit.pkl'
pickle.dump(etc, open(filename,'wb'))
```

Conclusion

In [145…

```
loaded_model=pickle.load(open('term_deposit.pkl','rb'))


original=np.array(y_test)
predicted=np.array(loaded_model.predict(x_test))
```

In [146…

```
accuracy_score(y_test,loaded_model.predict(x_test))
```

Out[146]: 0.9621408753244428

In [147…

```
df=pd.DataFrame({'Original':original,'Predicted':predicted})
df
```

Out[147]:

	Original	Predicted
0	0	0
1	0	0
2	0	0
3	1	1
4	0	0
...	...	...

11168	1	1
11169	0	0
11170	0	0
11171	0	1
11172	1	1

11173 rows × 2 columns

Lets make data frame for results on test data for all the model

In [148…

```
df=pd.DataFrame({'LogisticRegression':prediction_logr,
                 'GradientBoostingClassifier':prediction_gb,
                 'AdaBoostClassifier':prediction_ad,
                 'RandomForestClassifier':prediction_rfc,
                 'ExtraTreesClassifier':prediction_etc,
                'DecisionTreeClassifier':prediction_dtc,
                'tuned_etc':prediction_tuned_etc})
df
```

Out[148]:

	LogisticRegression	GradientBoostingClassifier	AdaBoostClassifier	RandomForestClassifier	ExtraTreesClassifi
0	0	0	0	0	
1	1	1	1	1	
2	1	1	1	1	
3	0	1	1	0	
4	0	0	0	0	
...	...	...	...	...	
13559	0	1	1	1	
13560	0	1	1	1	
13561	0	1	1	1	
13562	1	1	1	1	
13563	1	1	1	1	

13564 rows × 7 columns

Building a Predictive System

In [155…

```
test
```

Out[155]:

	age	job	marital	education	default	balance	housing	loan	contact	day
0	-0.830543	0.852310	-0.287967	-0.256082	-0.131336	-0.349877	0.893033	-0.429564	-0.726140	-0.001693
1	2.549644	0.365121	-1.884603	-1.737907	-0.131336	0.636076	-1.119779	-0.429564	1.085204	-2.093781
2	-0.959923	0.618588	1.372809	1.033920	-0.131336	-0.335968	0.893033	-0.429564	1.431917	0.115298

3	1.414890	0.852310	1.372809	-1.737907	-0.131336	0.940270	0.893033	-0.429564	1.085204	-0.242825
4	0.520126	-1.023489	-1.884603	-0.256082	-0.131336	-2.747632	-1.119779	2.327941	1.431917	-1.691501
...	...	...	...	...	...	...	...	...	...	..
13559	-0.038159	0.086458	-0.287967	1.033920	-0.131336	-0.392516	-1.119779	-0.429564	-0.726140	1.386449
13560	1.213253	-1.023489	-0.287967	-1.737907	-0.131336	0.473571	0.893033	-0.429564	1.431917	0.563344
13561	-0.468654	0.365121	-0.287967	-1.737907	-0.131336	-0.266423	0.893033	-0.429564	-0.726140	1.483967
13562	-1.233677	-1.613572	1.372809	-0.256082	-0.131336	-0.186352	-1.119779	-0.429564	-0.726140	-0.760845
13563	-1.233677	-1.613572	-0.287967	-0.256082	-0.131336	-0.424459	0.893033	-0.429564	-0.726140	-1.193781

13564 rows × 16 columns

In [ ]:
```
testcsv=test.to_csv()
```

In [156…
```
input_data=(-0.830543,0.852310,0.287967,0.256082,0.131336,
            0.349877,0.893033,0.429564,0.726140,0.001693,0.835121,
            2.060474,1.484674,0.479134,0.479073,0.476366)
ar_data=np.asarray(input_data)
reshaped=ar_data.reshape(1,-1)
pred=loaded_model.predict(reshaped)

if pred[0]==1:
    print('Person will subcribe to term deposit')
else:
    print('Person will not subcribe to term deposit')
```

```
Person will subcribe to term deposit
```

In [159…
```
input_data=(1.4148903595173163,0.8523104612088603,1.372809166013107,-1.7379074499444418,
            -0.13133597200737818,0.9402695721808009,0.8930333777833528,-0.42956416163759
            1.0852041983883653,-0.24282541194612356,0.8351205052311078,
            -1.0582101567942974,0.13339206173577844,-0.4791341542130769,-0.4790725614043
ar_data=np.asarray(input_data)
reshaped=ar_data.reshape(1,-1)
pred=loaded_model.predict(reshaped)

if pred[0]==1:
    print('Person will subcribe to term deposit')
else:
    print('Person will not subcribe to term deposit')
```

```
Person will not subcribe to term deposit
```

In [ ]: