MCS 7103_Assignment_one

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Predicting if a client will subscribe to a Term Deposit

Business problem:

There has been a revenue decline for the Portuguese bank, and they would like to know what actions to take. After investigation, we 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 a 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 a higher chance to subscribe for a term deposit and focus marketing effort on such clients.

Data Wrangling

The Data to be used to predict if a client will subscribe to A Term Deposit was obtained from https://archive.ics.uci.edu/dataset/222/bank+marketing

A classification approach is used to predict which clients are more likely to subscribe for term deposits.

[24]:
```
# import required python libray
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler, StandardScaler
```

[25]:
```
#Read data set
df=pd.read_csv("bank-full.csv",delimiter=';',quotechar='"')
```

Printing the first 5 rows of the dataset

[26]:
```
df.head()
```

[26]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
```

```
3   47   blue-collar  married    unknown      no      1506      yes   no
4   33       unknown   single    unknown      no         1       no   no

   contact  day month  duration  campaign  pdays  previous poutcome   y
0  unknown    5   may       261         1     -1         0  unknown  no
1  unknown    5   may       151         1     -1         0  unknown  no
2  unknown    5   may        76         1     -1         0  unknown  no
3  unknown    5   may        92         1     -1         0  unknown  no
4  unknown    5   may       198         1     -1         0  unknown  no
```

What's the size of Dataset

[27]:
```
df.shape
```

[27]:
```
(45211, 17)
```

The dataset consist of 45211 rows and 17 columns

What are the different fields and respective Datatypes that constitute the Dataset

[28]:
```
df.info()
```

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

Age: This is age of client of Numeric type

Job : This is client's title of categorical type

Marital: This is marital status for the customer(Categorical)

Education: This field shows the edcuation level for the client(Categorical)

default: whether customer has deafaulted credit or not(Binary)

balance: customer average yearly balance(Numeric) housing: whether a customer has a housing loan or not (Binary)

loan: Whether customer has personal loan or not (Binary)

contact: whether customer was contacted using cellular or telephone(categorical)

day: Last day of the month (Numeric)

Month: last contact month of year (categorical)

duration: Last contact duration, in seconds (numeric)

campaign: number of contacts performed during this campaign and for this client (numeric)

pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric, -1 means client was not previously contacted)

previous: number of contacts performed before this campaign and for this client (numeric)

poutcome: outcome of the previous marketing campaign (categorical: "unknown","other","failure","success")

y: has the client subscribed a term deposit? (binary: "yes","no")

find out duplication

[29]:
```
df.nunique()
```

[29]:
```
age            77
job            12
marital         3
education       4
default         2
balance      7168
housing         2
loan            2
contact         3
day            31
month          12
duration     1573
campaign       48
pdays         559
previous       41
poutcome        4
y               2
dtype: int64
```

Find out missing values in the dataset

[30]:
```
df.isnull().sum()
```

[30]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

EDA Exploratory Data Analysis

Univariate Analysis

Analysis of 'Subscribed' variable

[32]:
```
#Frequency of 'subscribed'
df['y'].value_counts()
```

[32]:
```
y
no     39922
yes     5289
Name: count, dtype: int64
```

[33]:
```
df1=df
```

[34]:
```
df1
```

[34]:
```
       age           job   marital  education default  balance housing loan  \
0       58    management   married   tertiary      no     2143     yes   no
1       44    technician    single  secondary      no       29     yes   no
2       33  entrepreneur   married  secondary      no        2     yes  yes
3       47   blue-collar   married    unknown      no     1506     yes   no
4       33       unknown    single    unknown      no        1      no   no
…     …            …        …         …         …       …     …   …
45206   51    technician   married   tertiary      no      825      no   no
45207   71       retired  divorced    primary      no     1729      no   no
```

```
45208   72       retired   married  secondary      no     5715      no   no
45209   57   blue-collar   married  secondary      no      668      no   no
45210   37  entrepreneur   married  secondary      no     2971      no   no

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

[45211 rows x 17 columns]
```

Converting the target variables into 0s and 1s

[35]:
```python
df1['y'] = df1['y'].map({'yes': 1, 'no': 0})
```

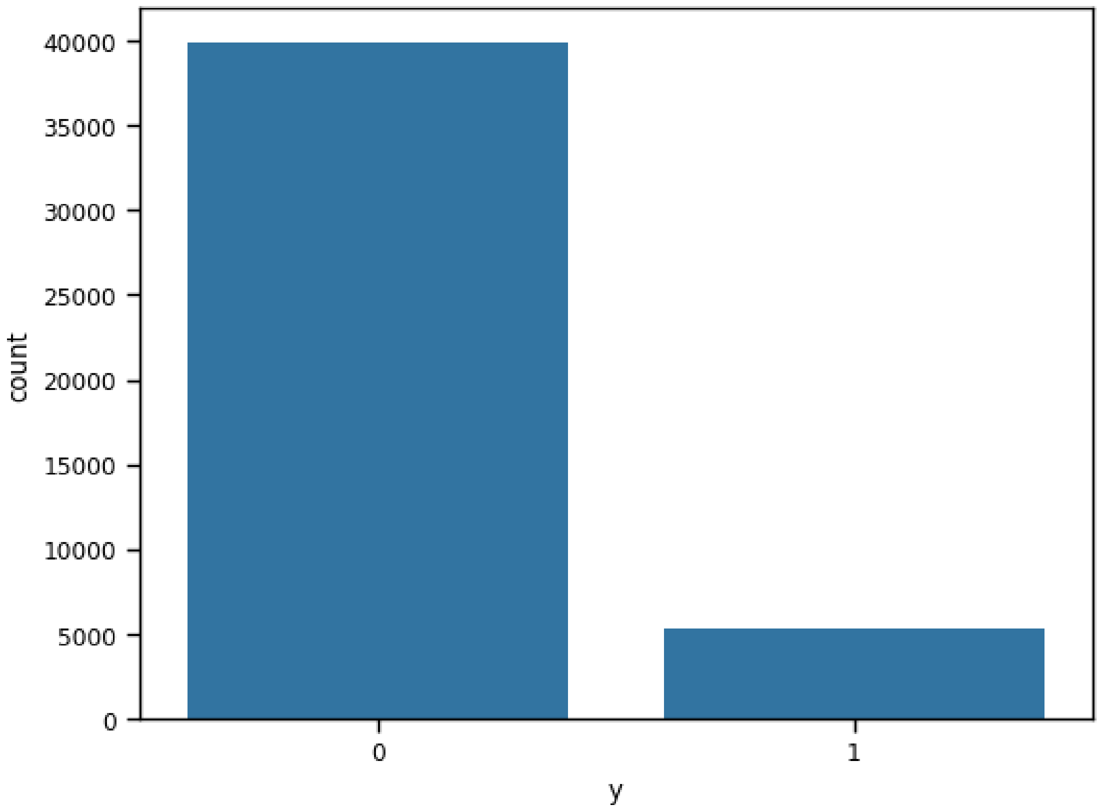
[36]:
```python
df1
```

[36]:
```
       age           job   marital  education default  balance housing loan  \
0       58    management   married   tertiary      no     2143     yes   no
1       44    technician    single  secondary      no       29     yes   no
2       33  entrepreneur   married  secondary      no        2     yes  yes
3       47   blue-collar   married    unknown      no     1506     yes   no
4       33       unknown    single    unknown      no        1      no   no
…      …           …       …        …       …        …      …    …
45206   51    technician   married   tertiary      no      825      no   no
45207   71       retired  divorced    primary      no     1729      no   no
45208   72       retired   married  secondary      no     5715      no   no
45209   57   blue-collar   married  secondary      no      668      no   no
45210   37  entrepreneur   married  secondary      no     2971      no   no

         contact  day month  duration  campaign  pdays  previous poutcome  y
0        unknown    5   may       261         1     -1         0  unknown  0
1        unknown    5   may       151         1     -1         0  unknown  0
2        unknown    5   may        76         1     -1         0  unknown  0
3        unknown    5   may        92         1     -1         0  unknown  0
4        unknown    5   may       198         1     -1         0  unknown  0
…            …    …   …        …         …      …       …        … ..
45206   cellular   17   nov       977         3     -1         0  unknown  1
45207   cellular   17   nov       456         2     -1         0  unknown  1
```

```
45208   cellular   17   nov      1127          5     184           3  success  1
45209  telephone   17   nov       508          4      -1           0  unknown  0
45210   cellular   17   nov       361          2     188          11    other  0

[45211 rows x 17 columns]
```

[46]:
```python
# Plotting the 'subscribed' frequency
sns.countplot(data=df1, x=df1['y'])
```

[46]:
```
<Axes: xlabel='y', ylabel='count'>
```



[47]:
```python
df1['y'].value_counts(normalize=True)
```

[47]:
```
y
0    0.883015
1    0.116985
Name: proportion, dtype: float64
```

From the above analysis we can see that roughly 12% subscribed to term deposit

Analysing th ‘Job’ variable

[42]:

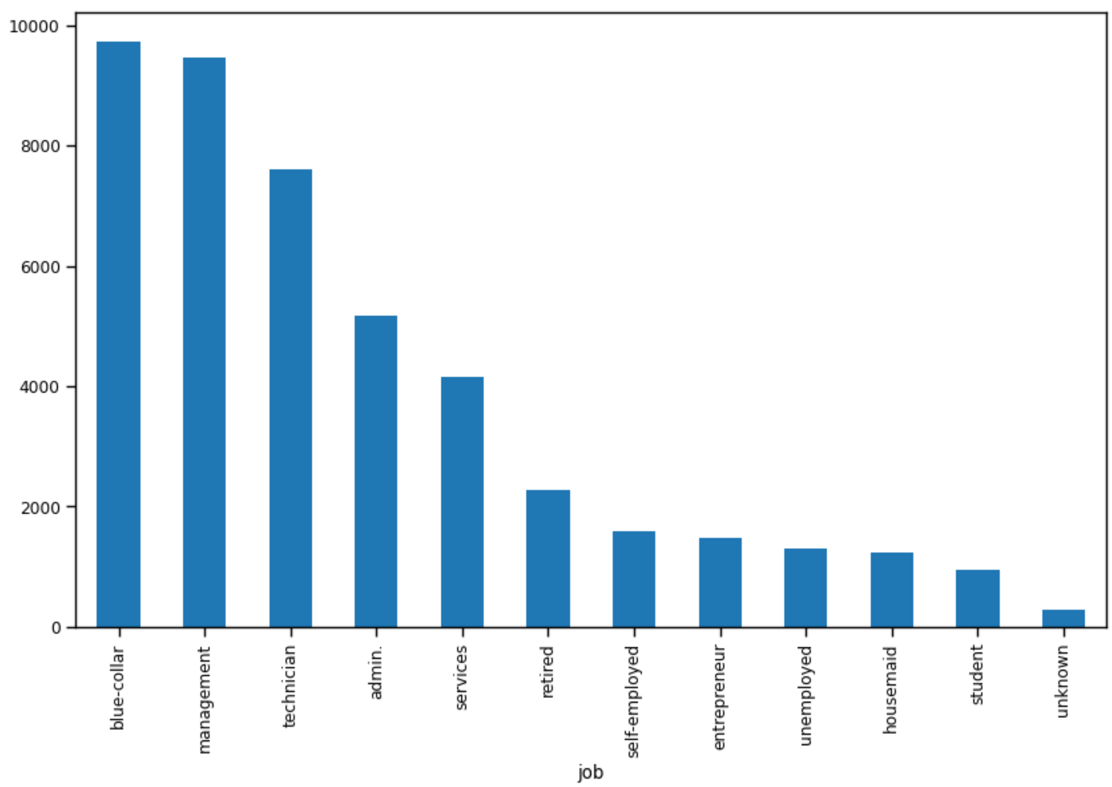
```
#Frequency table
df1['job'].value_counts()
```

[42]:

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

[43]:

```
# Plotting the job frequency table
sns.set_context('paper')
df1['job'].value_counts().plot(kind='bar', figsize=(10,6));
```



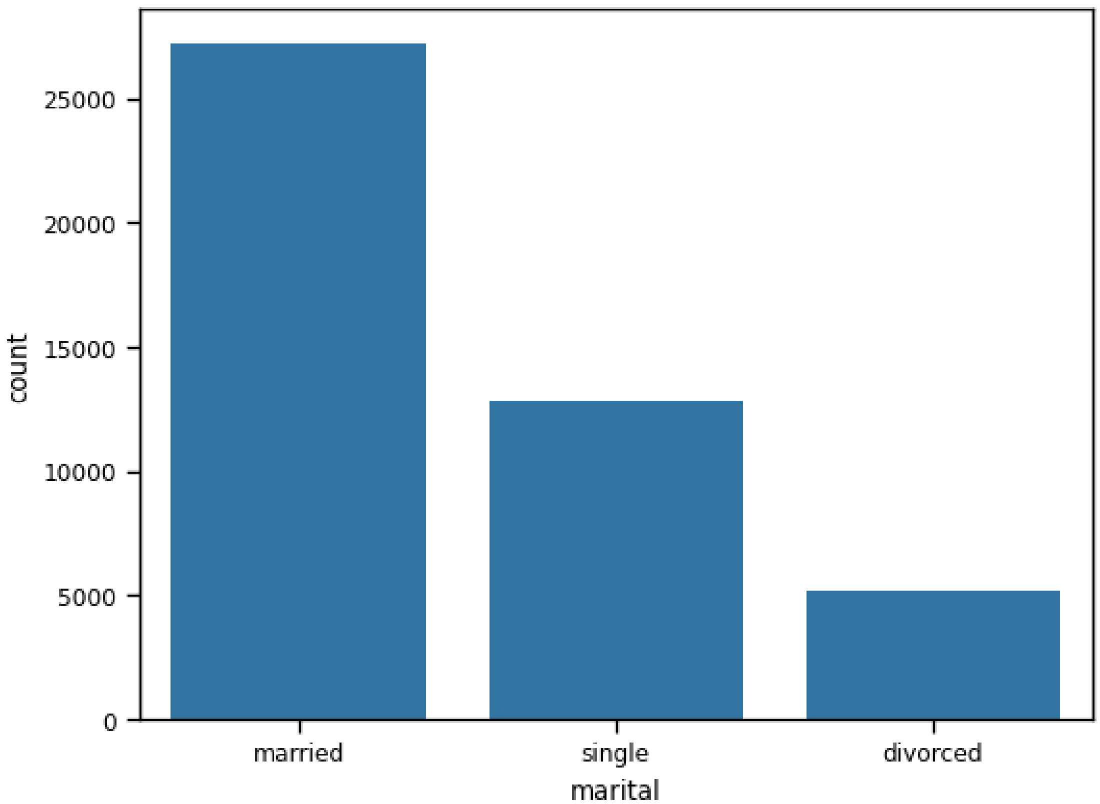
Most of the clients belonged to blue-collar job and students are least in general as they don't make term deposits in general.

Analysis of 'marital' status

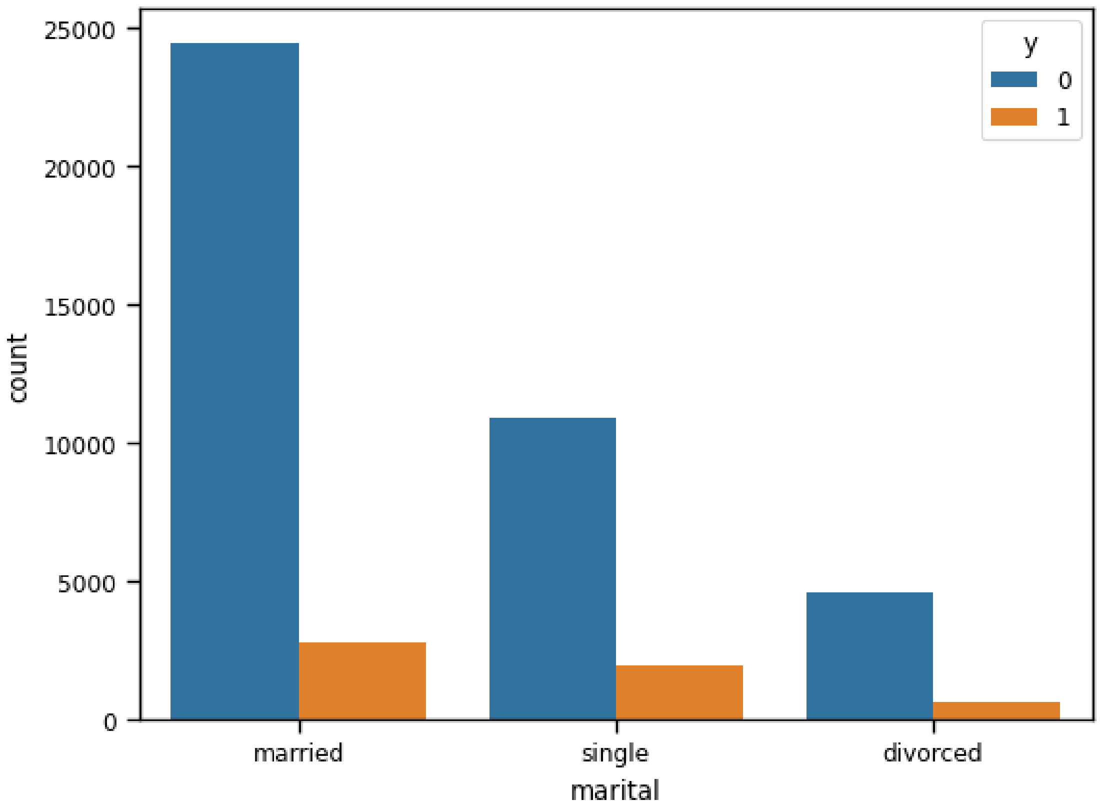
[44]:
```
df1['marital'].value_counts()
```

[44]:
```
marital
married     27214
single      12790
divorced     5207
Name: count, dtype: int64
```

[45]:
```
sns.countplot(data=df1, x='marital');
```



[49]:
```
sns.countplot(data=df1, x='marital', hue='y');
```

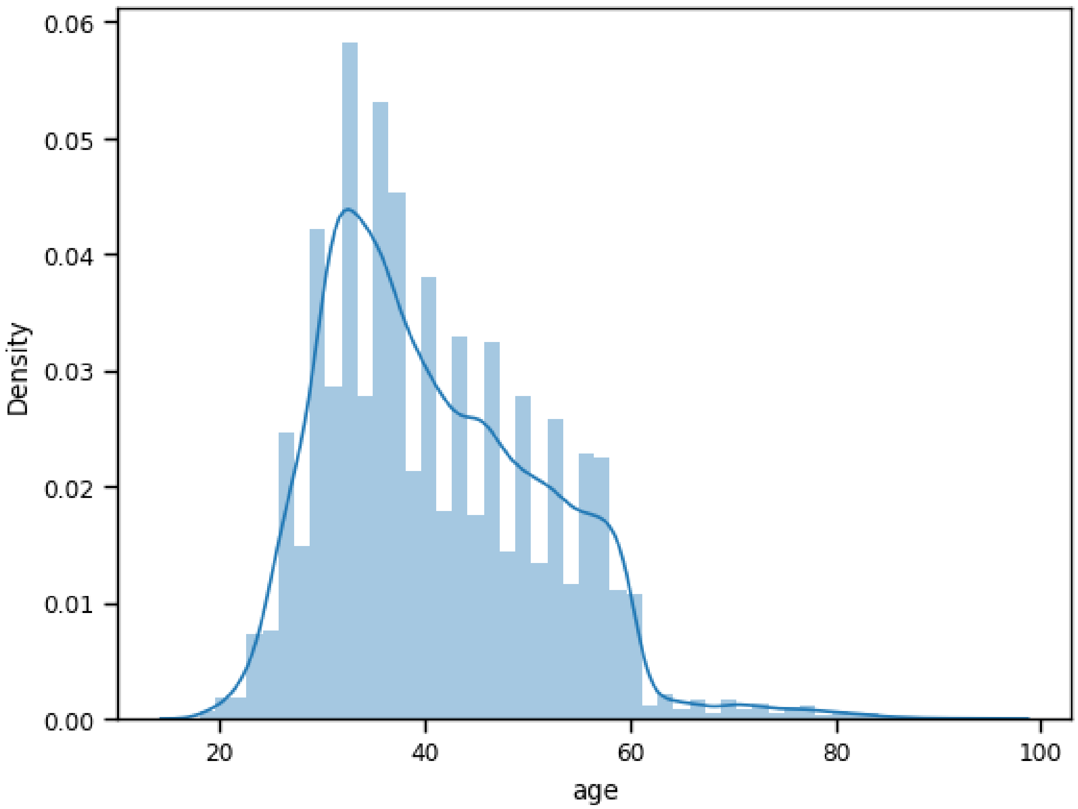


from the above graph, married subscribed more to term deposit, followed by single, lastly divorced

Analyzing the 'age' variable

[50]:
```
sns.distplot(df1['age']);
```

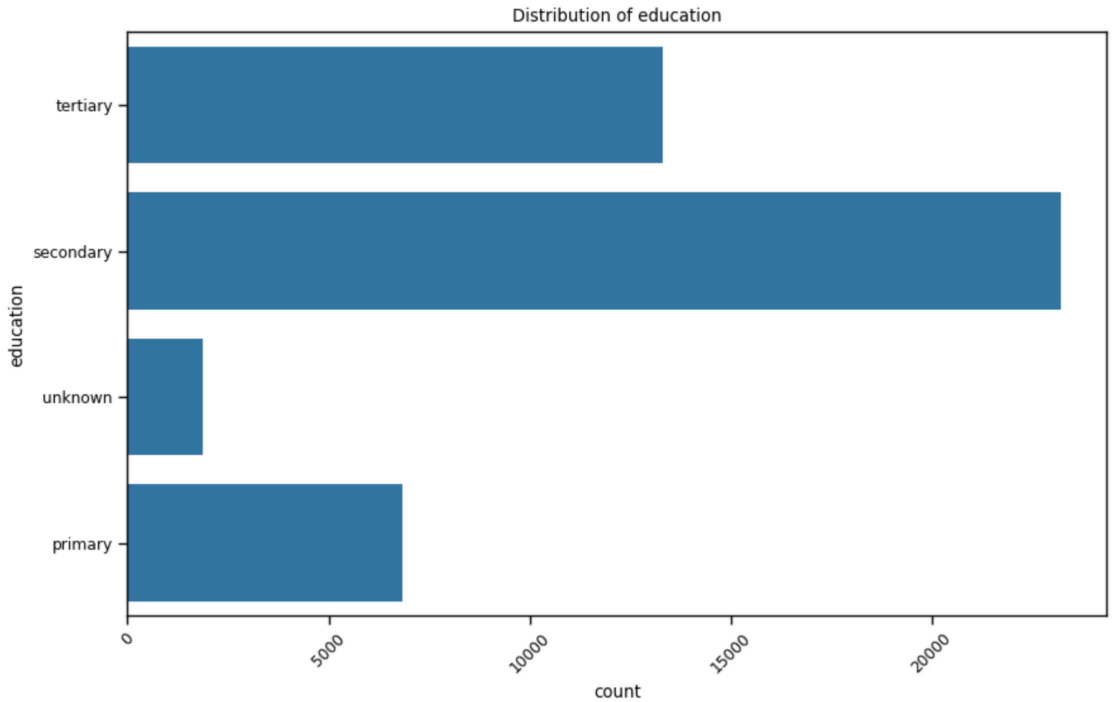
```
/tmp/ipykernel_5136/1708864848.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df1['age']);
```

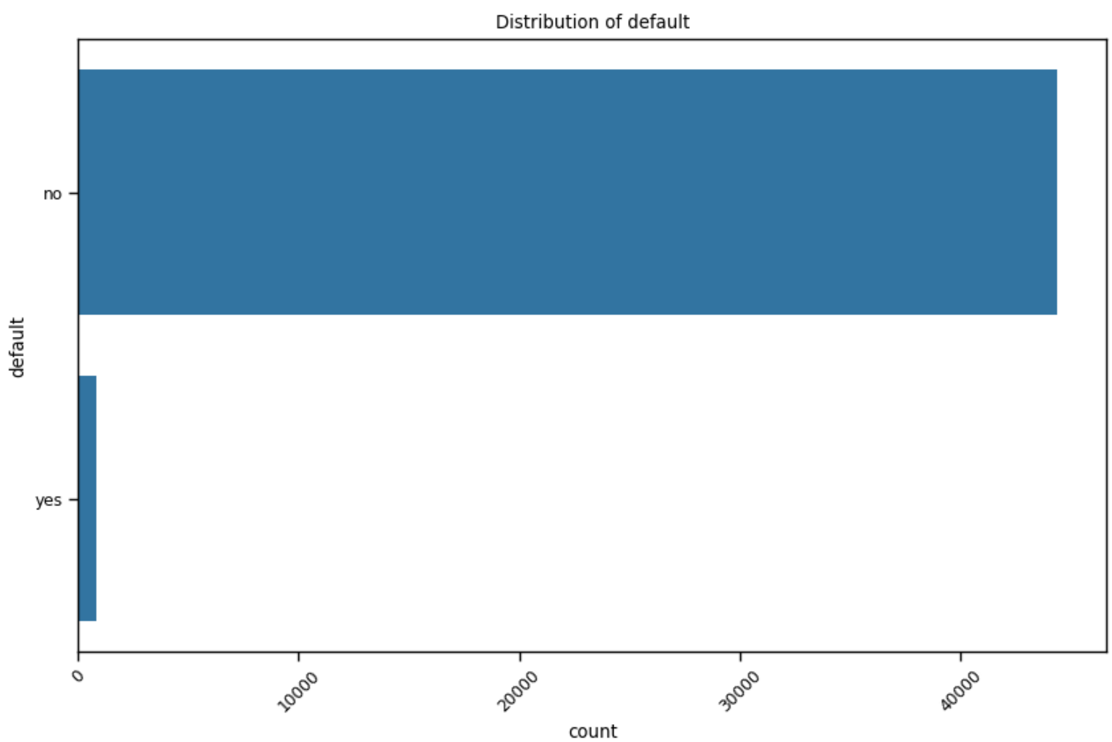


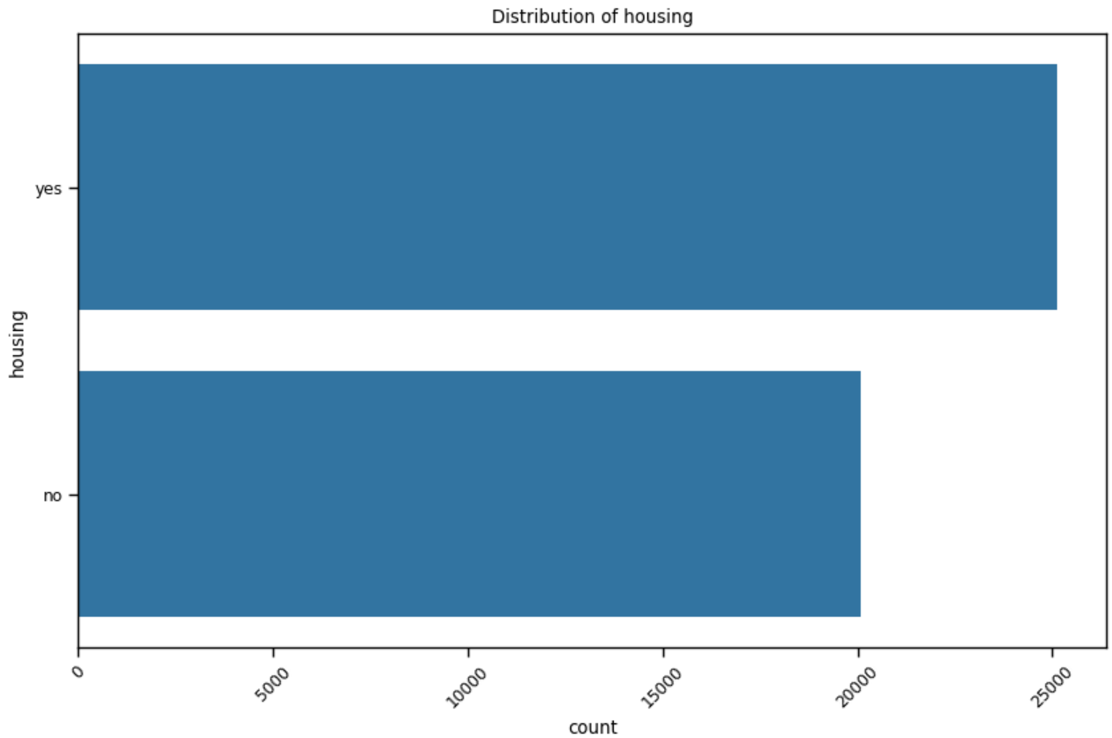
Most of the clients fall in the age group between 20-60.

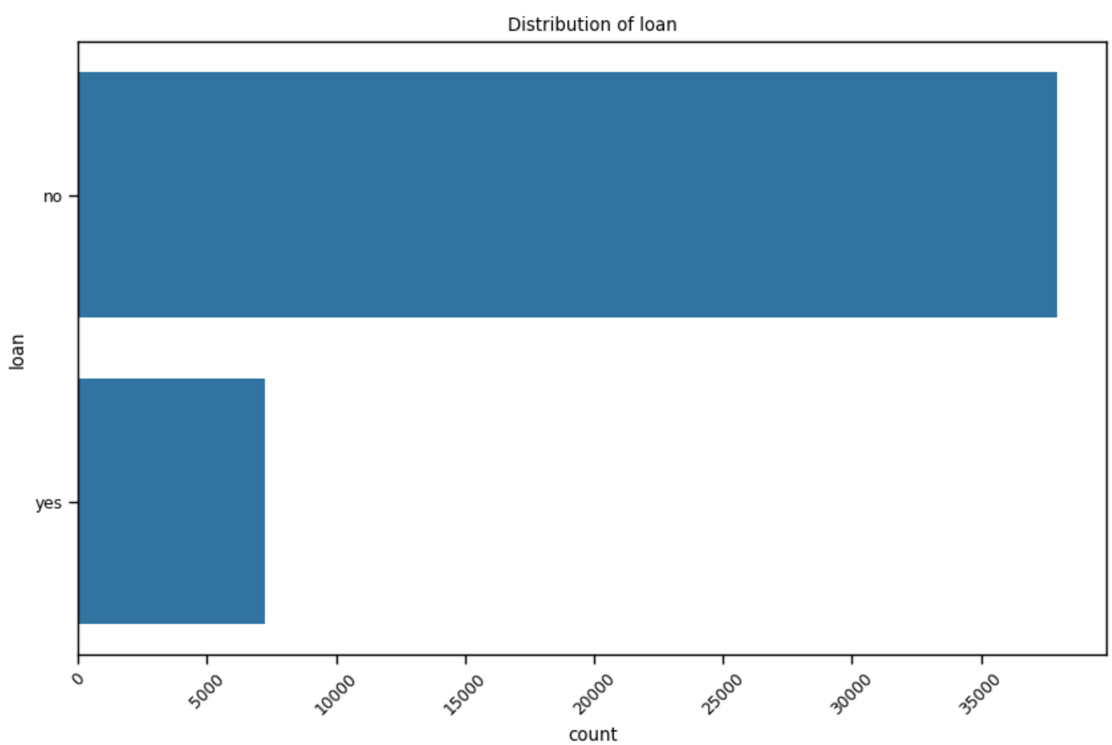
Distribution of other categorical values

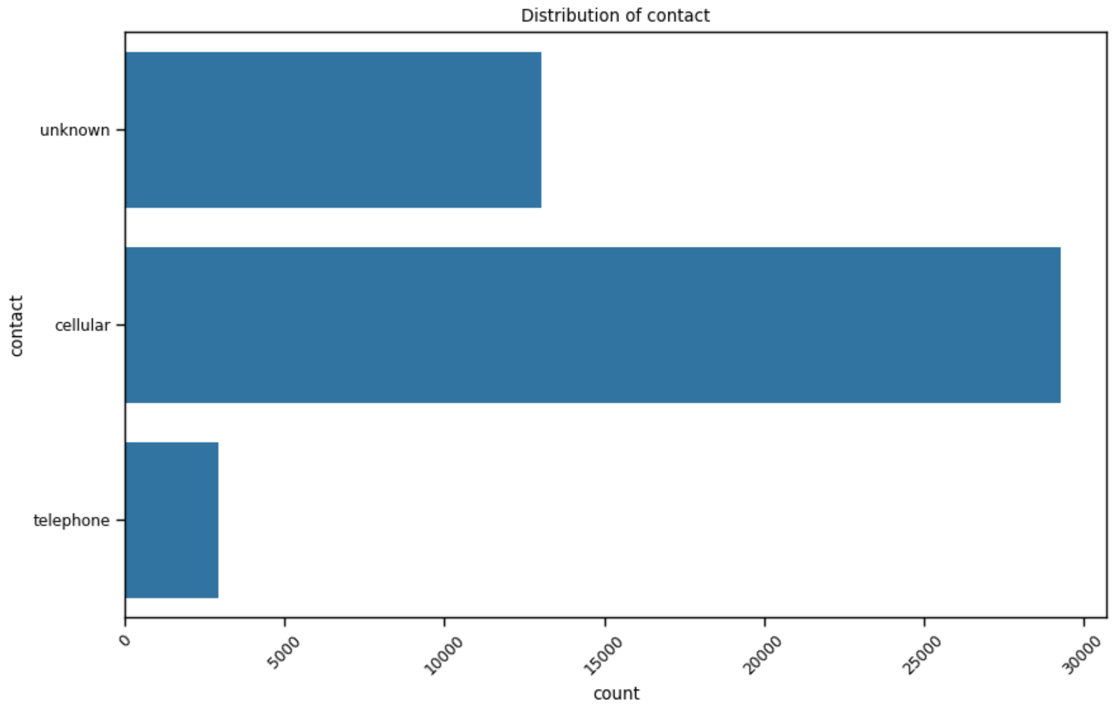
[74]:
```
categorical_features = [ 'education', 'default', 'housing', 'loan', 'contact',␣
    ↪'month', 'poutcome', 'y']
for feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.countplot(df[feature])
    plt.title(f'Distribution of {feature}')
    plt.xticks(rotation=45)
    plt.show()
```

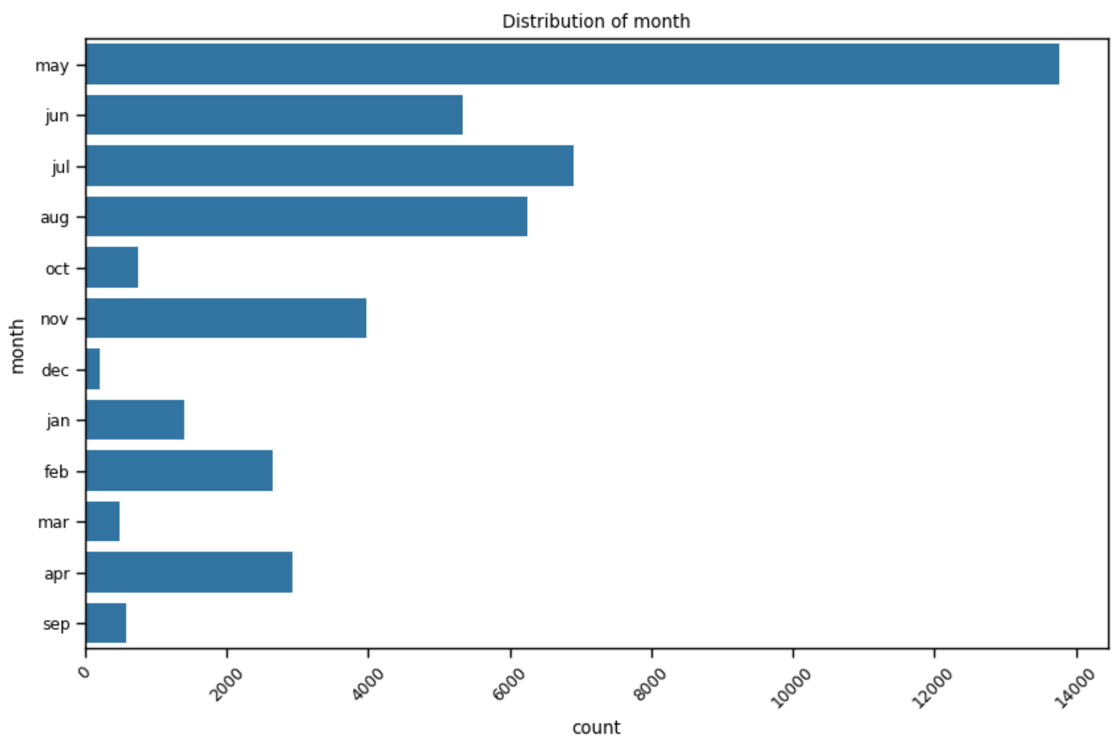

Distribution of education
tertiary
secondary
unknown
primary
education
0
5000
10000
15000
20000
count

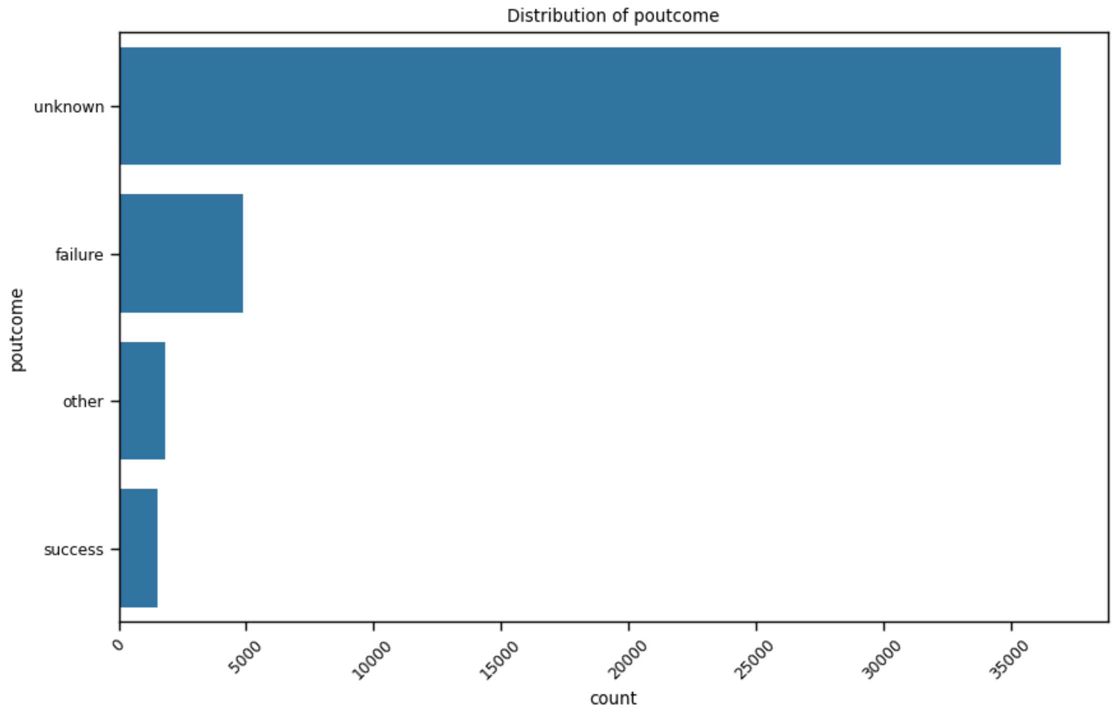

Distribution of default
no
yes
default
0
10000
20000
30000
40000
count

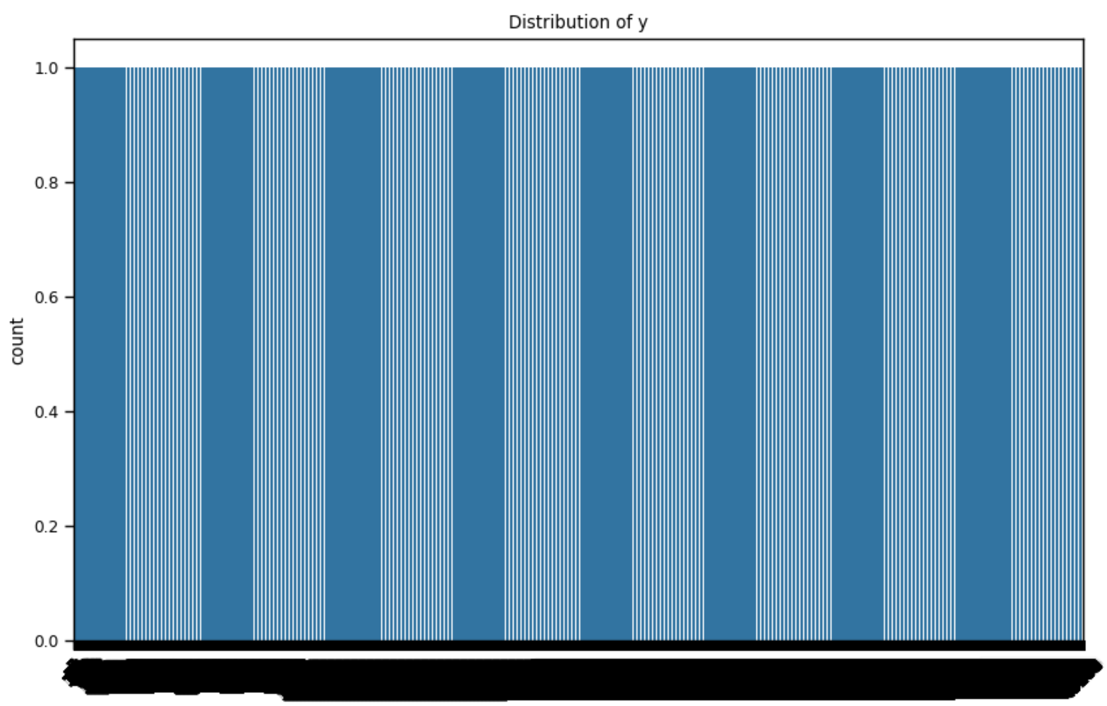

Distribution of housing
yes
no
housing
0
5000
10000
15000
20000
25000
count


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


Distribution of contact
unknown
cellular
telephone
contact
0
5000
10000
15000
20000
25000
30000
count


Distribution of month
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
month
0
2000
4000
6000
8000
10000
12000
14000
count





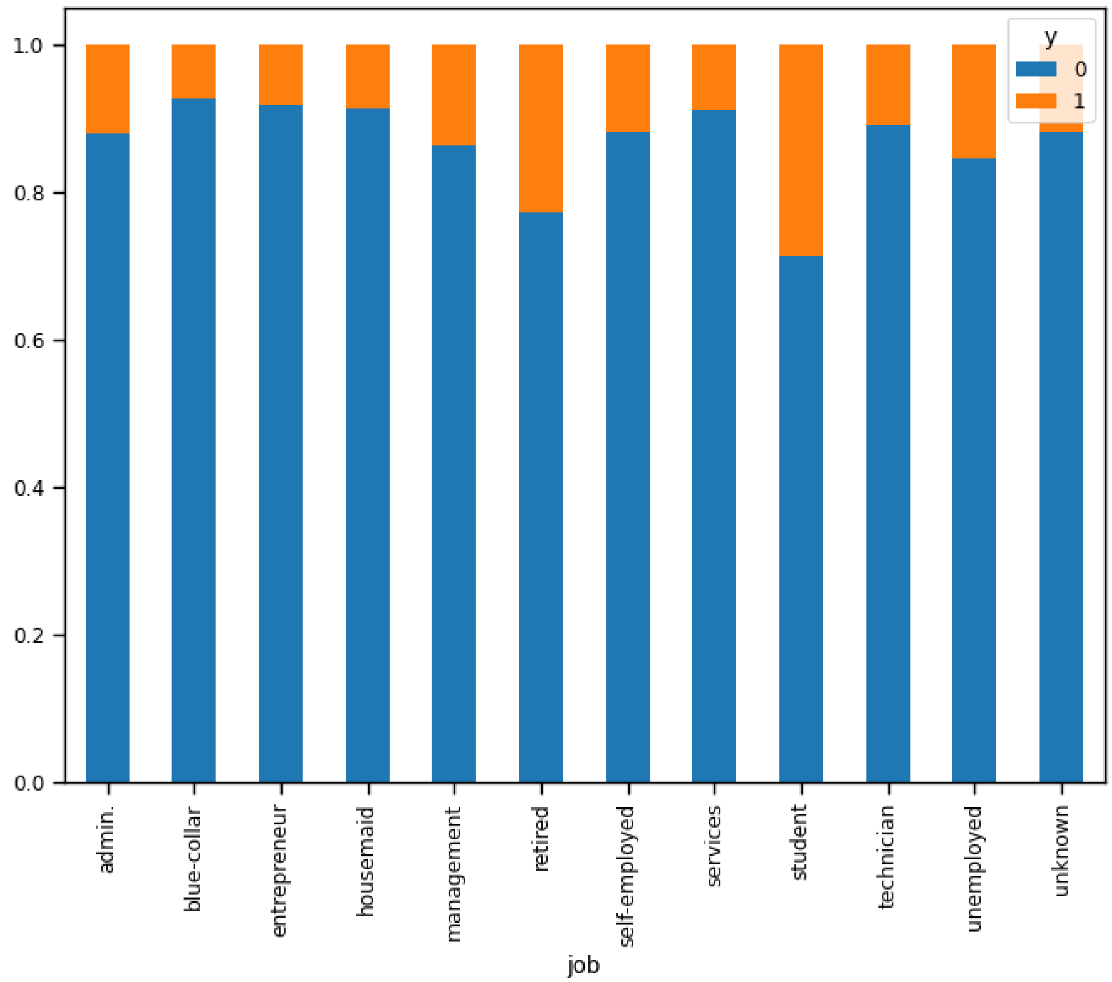
Bivariate Analysis

[52]:
```
#job vs subscribed
print(pd.crosstab(df1['job'],df1['y']))
```

```
y                 0     1
job
admin.         4540   631
blue-collar    9024   708
entrepreneur   1364   123
housemaid      1131   109
management     8157  1301
retired        1748   516
self-employed  1392   187
services       3785   369
student         669   269
technician     6757   840
unemployed     1101   202
unknown         254    34
```

[54]:
```
job = pd.crosstab(df1['job'],df1['y'])
job_norm = job.div(job.sum(1).astype(float), axis=0)
```

[55]:
```
job_norm.plot.bar(stacked=True,figsize=(8,6));
```



students and retired people have higher chances of subscribing to a term deposit, which is surprising as students generally do not subscribe to a term deposit. The possible reason is that the number of students in the dataset is less and comparatively to other job types, more students have subscribed to a term deposit.

[56]:
```
#Marital status vs subscribed
pd.crosstab(df1['marital'], df1['y'])
```

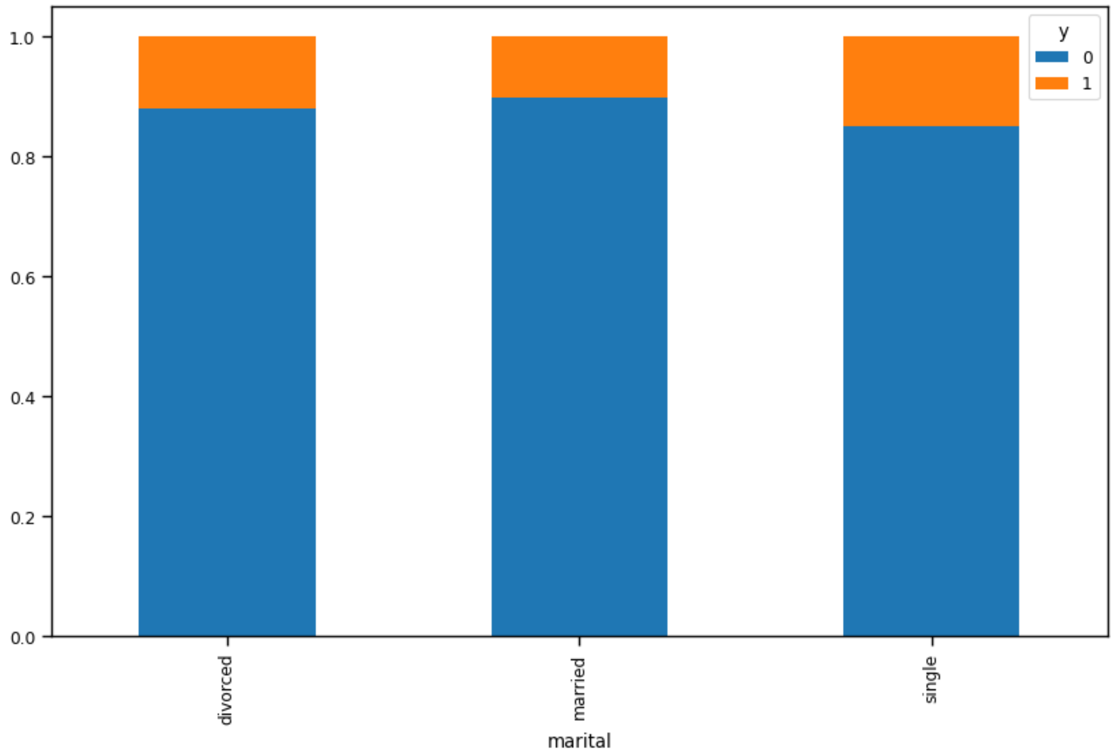
[56]:
```
y              0     1
marital
divorced    4585   622
married    24459  2755
single     10878  1912
```

[57]:
```
marital = pd.crosstab(df['marital'], df['y'])
marital_norm = marital.div(marital.sum(1).astype(float), axis=0)
```

```
marital_norm
```

[57]:
```
y                0         1
marital
divorced  0.880545  0.119455
married   0.898765  0.101235
single    0.850508  0.149492
```

[58]:
```
marital_norm.plot.bar(stacked=True, figsize=(10,6));
```



From the above analysis we can infer that marital status doesn't have a major impact on the subscription to term deposits.

[60]:
```
#default vs subscription
pd.crosstab(df1['default'], df1['y'])
```

[60]:
```
y            0     1
default
no       39159  5237
yes        763    52
```

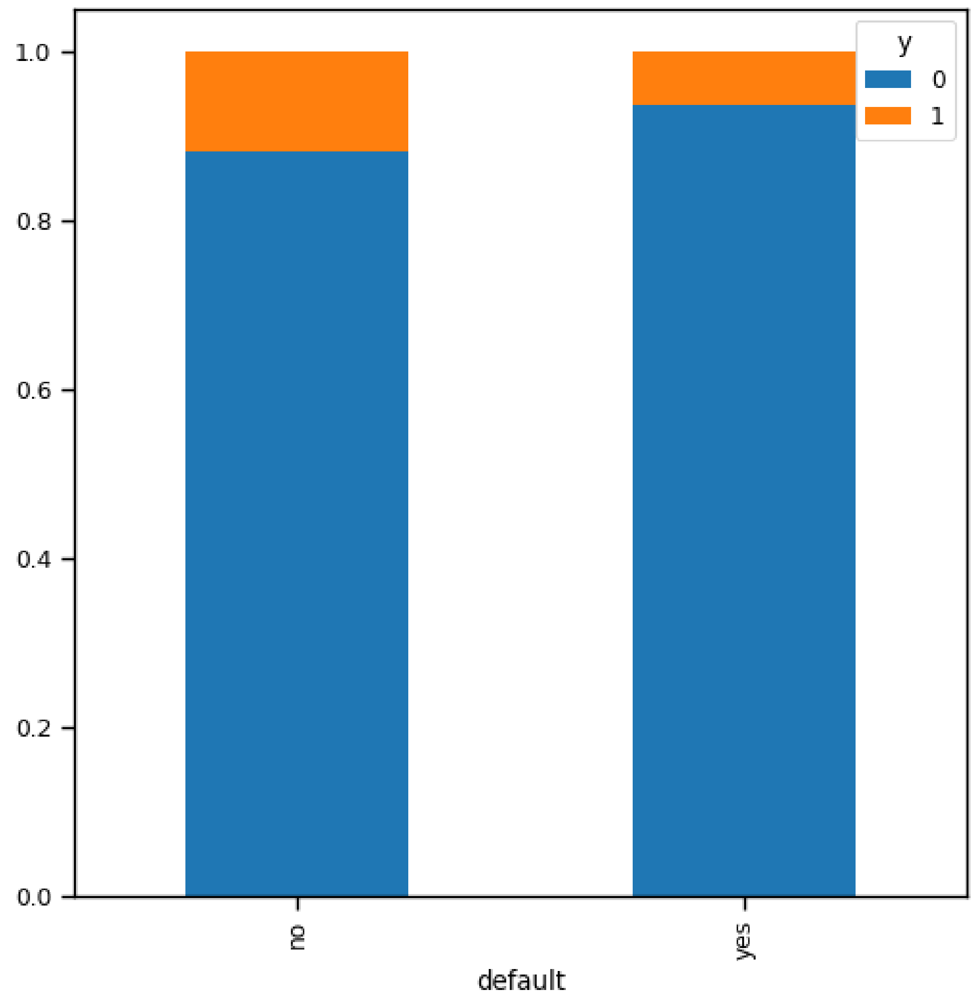
[62]:
```
dflt = pd.crosstab(df1['default'], df1['y'])
dflt_norm = dflt.div(dflt.sum(1).astype(float), axis=0)
```

```
dflt_norm
```

[62]:
```
y               0         1
default
no       0.882039  0.117961
yes      0.936196  0.063804
```

[63]:
```
dflt_norm.plot.bar(stacked=True, figsize=(6,6))
```

[63]: <Axes: xlabel='default'>



clients having no previous default have slightly higher chances of subscribing to a term loan as compared to the clients who have previous default history.

[67]:
```
#Correlation matrix
corr_column=['age','balance','day','duration','campaign','pdays','previous','y']
```

```
cor = df1[corr_column].corr()
cor
```

[67]:

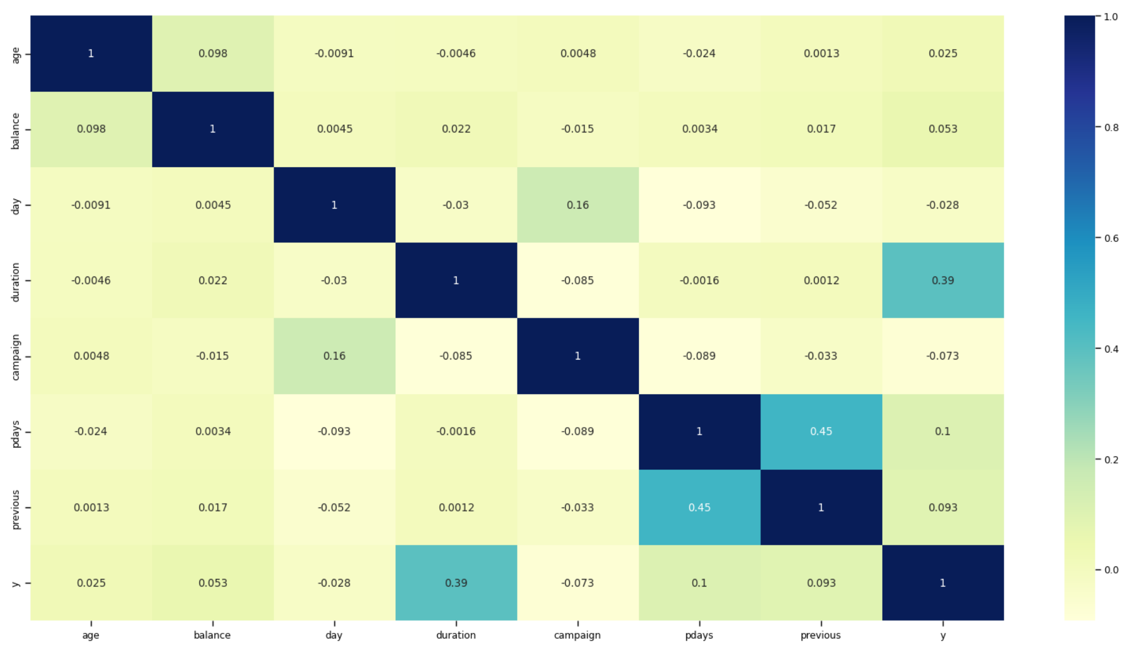
```
               age   balance       day  duration  campaign     pdays  \
age       1.000000  0.097783 -0.009120 -0.004648  0.004760 -0.023758
balance   0.097783  1.000000  0.004503  0.021560 -0.014578  0.003435
day      -0.009120  0.004503  1.000000 -0.030206  0.162490 -0.093044
duration -0.004648  0.021560 -0.030206  1.000000 -0.084570 -0.001565
campaign  0.004760 -0.014578  0.162490 -0.084570  1.000000 -0.088628
pdays    -0.023758  0.003435 -0.093044 -0.001565 -0.088628  1.000000
previous  0.001288  0.016674 -0.051710  0.001203 -0.032855  0.454820
y         0.025155  0.052838 -0.028348  0.394521 -0.073172  0.103621

          previous         y
age       0.001288  0.025155
balance   0.016674  0.052838
day      -0.051710 -0.028348
duration  0.001203  0.394521
campaign -0.032855 -0.073172
pdays     0.454820  0.103621
previous  1.000000  0.093236
y         0.093236  1.000000
```

[68]:

```
fig,ax= plt.subplots()
fig.set_size_inches(20,10)
sns.heatmap(cor, annot=True, cmap='YlGnBu')
```

[68]:

```
<Axes: >
```



The duration of the call is highly correlated with the target variable. As the duration of the call is more, there are higher chances that the client is showing interest in the term deposit and hence there are higher chances that the client will subscribe to term deposit.

Conclustion:

More Job types are Admin, Technician, and blue-collar and it means bank targeting high salaried people.

Most customer were contacted using cellular

Most of the clients fall in the age group between 20-60.

12% of the total client subscribed to term deposit

most of the clients belonged to blue-collar job and students are least in general as they don't make term deposits in general.

clients having no previous default have slightly higher chances of subscribing to a term loan as compared to the clients who have previous default history.

students and retired people have higher chances of subscribing to a term deposit, which is surprising as students generally do not subscribe to a term deposit. The possible reason is that the number of students in the dataset is less and comparatively to other job types, more students have subscribed to a term deposit.

[ ]:

```

```