```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_excel('/content/bank term deposit.xlsx')
```

```
df.sample(5)
```

| | Age | Job | Marital | Education | Default | housing | Loan | Contact | Month | day_of_week | ... | campaign | pdays | previo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5964** | 52 | unknown | married | basic.4y | no | no | no | telephone | may | tue | ... | 1 | 999 | |
| **20225** | 29 | technician | married | university.degree | unknown | yes | no | cellular | aug | mon | ... | 2 | 999 | |
| **39261** | 80 | retired | married | basic.4y | no | no | no | cellular | mar | fri | ... | 3 | 6 | |
| **17267** | 59 | retired | married | basic.9y | unknown | no | no | cellular | jul | fri | ... | 3 | 999 | |
| **10849** | 38 | admin. | single | university.degree | no | yes | no | telephone | jun | wed | ... | 2 | 999 | |

5 rows × 21 columns

## data information

1 - Age - Age of the customer and it's a numerical variable.

2 - Job- The type of job a customer does and it's a categorical variable.

3 - Marital : It's self explanatory. It demonstrates the customer's marital status and is a categorical variable.

4 - Education - Educational level of a customer and it's a categorical variable.

5 - Default :Showcases if a cx has credit in default? (Categorical).

6 - housing: Tells you If a cx has a housing loan.(categorical).

7 - loan: Demonstrates you If a cx has a Personal loan (categorical).

8 - contact: contact communication type (categorical).

9 - month: last contact month of year (categorical).

10 - day_of_week: last contact day of the week (categorical).

11 - duration: last contact duration, in seconds (numeric).

12 - campaign: number of contacts performed for this client during this campaign (numeric).

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric).

14 - previous: number of contacts performed for this client before this campaign(numeric).

15 - poutcome: outcome of the previous marketing campaign (categorical).

16 - empvarrate: employment variation rate - quarterly indicator (numeric).

17 - conspriceidx: consumer price index - monthly indicator (numeric).

18 - consconfidx: consumer confidence index - monthly indicator (numeric).

19 - euribor3m: euribor 3 month rate - daily indicator (numeric).

20 - nremployed: number of employees - quarterly indicator (numeric).

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

```
df.shape
```

```
(41188, 21)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Age           41188 non-null  int64
 1   Job           41188 non-null  object
 2   Marital       41188 non-null  object
 3   Education     41188 non-null  object
 4   Default       41188 non-null  object
 5   housing       41188 non-null  object
 6   Loan          41188 non-null  object
 7   Contact       41188 non-null  object
 8   Month         41188 non-null  object
 9   day_of_week   41188 non-null  object
 10  duration      41188 non-null  int64
 11  campaign      41188 non-null  int64
 12  pdays         41188 non-null  int64
 13  previous      41188 non-null  int64
 14  poutcome      41188 non-null  object
 15  empvarrate    41188 non-null  float64
 16  conspriceidx  41188 non-null  float64
 17  consconfidx   41188 non-null  float64
 18  euribor3m     41188 non-null  float64
 19  nremployed    41188 non-null  float64
 20  y             41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

```
# here are not any null values any columns
df.isnull().sum()
```

```
Age            0
Job            0
Marital        0
Education      0
Default        0
housing        0
Loan           0
Contact        0
Month          0
day_of_week    0
duration       0
campaign       0
pdays          0
previous       0
poutcome       0
empvarrate     0
conspriceidx   0
consconfidx    0
euribor3m      0
nremployed     0
y              0
dtype: int64
```

```
df.duplicated().sum()
```

```
12
```

here are 12 duplicate rows

```
# remove duplicate rows
df.drop_duplicates(inplace=True)
```

```
df.nunique()
```

```
Age              78
Job              12
Marital           4
Education         8
Default           3
housing           3
Loan              3
Contact           2
Month            10
day_of_week       5
duration       1544
campaign         42
```

```
pdays             27
previous           8
poutcome           3
empvarrate        10
conspriceidx      26
consconfidx       26
euribor3m        316
nremployed        11
y                  2
dtype: int64
```

```
# find unique values each columns
pd.Series({col: df[col].unique() for col in df.columns})
```

```
Age             [56, 57, 37, 40, 45, 59, 41, 24, 25, 29, 35, 5...
Job             [housemaid, services, admin., blue-collar, tec...
Marital                      [married, single, divorced, unknown]
Education       [basic.4y, high.school, basic.6y, basic.9y, pr...
Default                                       [no, unknown, yes]
housing                                       [no, yes, unknown]
Loan                                          [no, yes, unknown]
Contact                                    [telephone, cellular]
Month           [may, jun, jul, aug, oct, nov, dec, mar, apr, ...
day_of_week                            [mon, tue, wed, thu, fri]
duration        [261, 149, 226, 151, 307, 198, 139, 217, 380, ...
campaign        [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 19...
pdays           [999, 6, 4, 3, 5, 1, 0, 10, 7, 8, 9, 11, 2, 12...
previous                                [0, 1, 2, 3, 4, 5, 6, 7]
poutcome                          [nonexistent, failure, success]
empvarrate      [1.1, 1.4, -0.1, -0.2, -1.8, -2.9, -3.4, -3.0,...
conspriceidx    [93.994, 94.465, 93.918, 93.444, 93.798, 93.2,...
consconfidx     [-36.4, -41.8, -42.7, -36.1, -40.4, -42.0, -45...
euribor3m       [4.857, 4.856, 4.855, 4.859, 4.86, 4.858, 4.86...
nremployed      [5191.0, 5228.1, 5195.8, 5176.3, 5099.1, 5076....
y                                                      [no, yes]
dtype: object
```

```
df.columns
```

```
Index(['Age', 'Job', 'Marital', 'Education', 'Default', 'housing', 'Loan',
       'Contact', 'Month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'empvarrate', 'conspriceidx', 'consconfidx',
       'euribor3m', 'nremployed', 'y'],
      dtype='object')
```

```
df.dtypes
```

```
Age             int64
Job            object
Marital        object
Education      object
Default        object
```

```
housing          object
Loan             object
Contact          object
Month            object
day_of_week      object
duration          int64
campaign          int64
pdays             int64
previous          int64
poutcome         object
empvarrate      float64
conspriceidx    float64
consconfidx     float64
euribor3m       float64
nremployed      float64
y                object
dtype: object
```

```
df.describe()
```

| | Age | duration | campaign | pdays | previous | empvarrate | conspriceidx | consconfidx | euribor3m |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 41176.00000 | 41176.000000 | 41176.000000 | 41176.000000 | 41176.000000 | 41176.000000 | 41176.000000 | 41176.000000 | 41176.000000 |
| **mean** | 40.02380 | 258.315815 | 2.567879 | 962.464810 | 0.173013 | 0.081922 | 93.575720 | -40.502863 | 3.621293 |
| **std** | 10.42068 | 259.305321 | 2.770318 | 186.937102 | 0.494964 | 1.570883 | 0.578839 | 4.627860 | 1.734437 |
| **min** | 17.00000 | 0.000000 | 1.000000 | 0.000000 | 0.000000 | -3.400000 | 92.201000 | -50.800000 | 0.634000 |
| **25%** | 32.00000 | 102.000000 | 1.000000 | 999.000000 | 0.000000 | -1.800000 | 93.075000 | -42.700000 | 1.344000 |
| **50%** | 38.00000 | 180.000000 | 2.000000 | 999.000000 | 0.000000 | 1.100000 | 93.749000 | -41.800000 | 4.857000 |
| **75%** | 47.00000 | 319.000000 | 3.000000 | 999.000000 | 0.000000 | 1.400000 | 93.994000 | -36.400000 | 4.961000 |
| **max** | 98.00000 | 4918.000000 | 56.000000 | 999.000000 | 7.000000 | 1.400000 | 94.767000 | -26.900000 | 5.045000 |

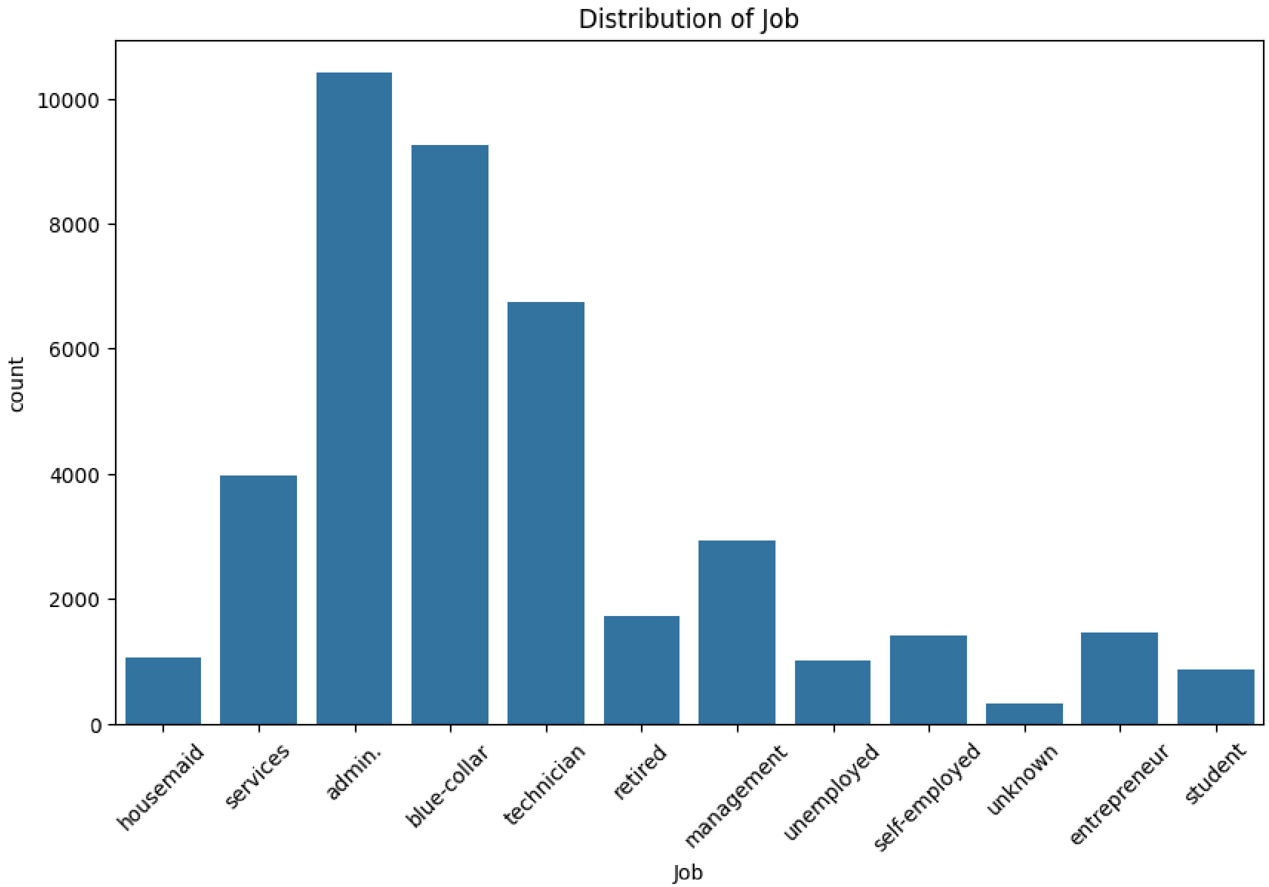
```
df.describe(include='object')
```

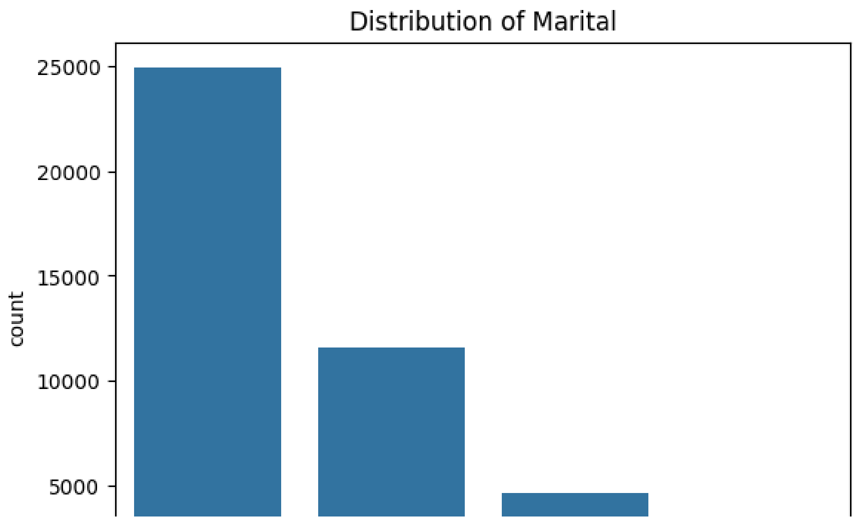
| | Job | Marital | Education | Default | housing | Loan | Contact | Month | day_of_week | poutcome | y |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 | 41176 |
| **unique** | 12 | 4 | 8 | 3 | 3 | 3 | 2 | 10 | 5 | 3 | 2 |
| **top** | admin. | married | university.degree | no | yes | no | cellular | may | thu | nonexistent | no |
| **freq** | 10419 | 24921 | 12164 | 32577 | 21571 | 33938 | 26135 | 13767 | 8618 | 35551 | 36537 |

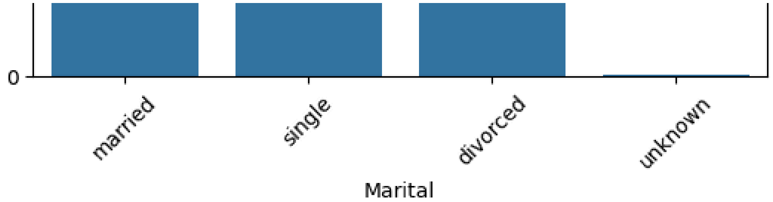
```
df['y'].value_counts()
```

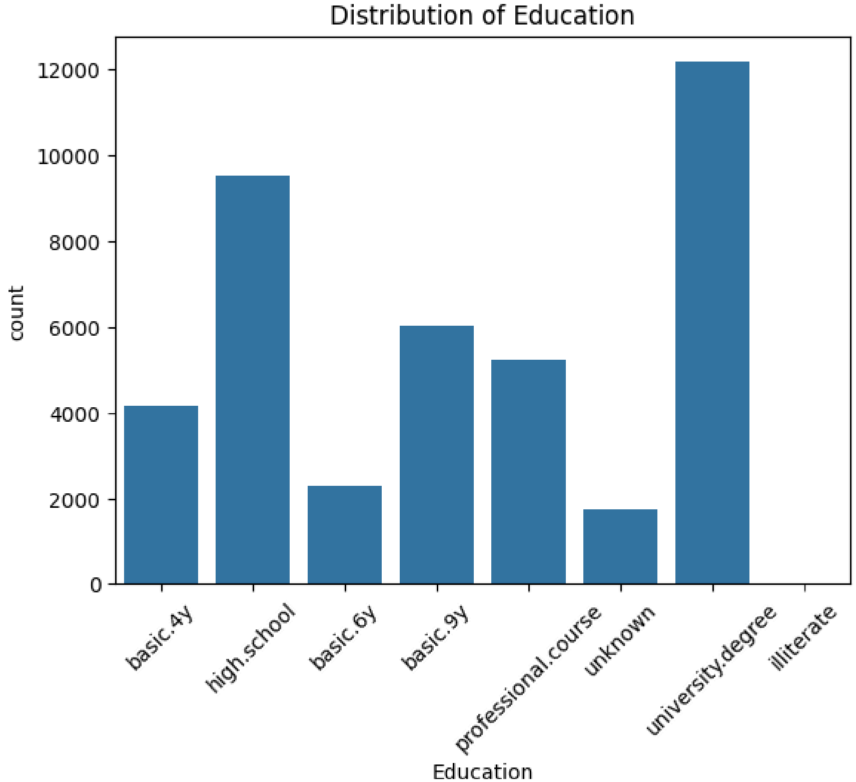
```
no     36537
yes     4639
Name: y, dtype: int64
```

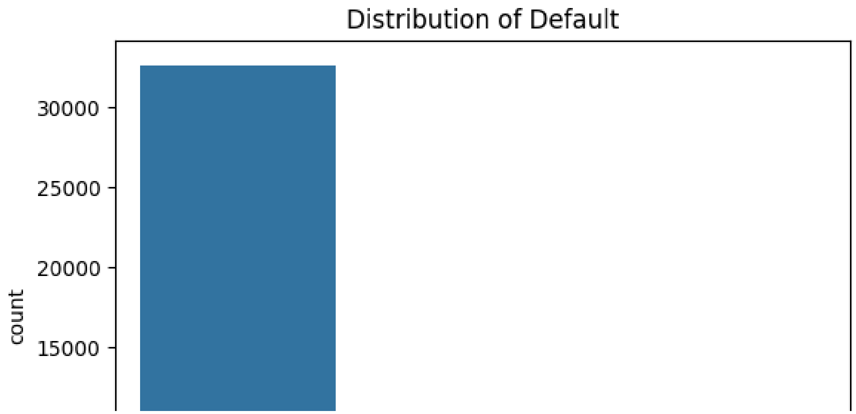
```
# Categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns

plt.figure(figsize=(10,6))
for col in categorical_columns:
    sns.countplot(x=col, data=df)
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.show()
```

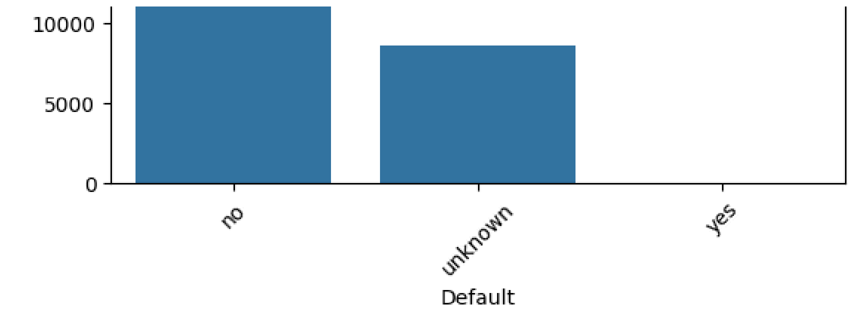

Distribution of Job
count
10000
8000
6000
4000
2000
0
housemaid
services
admin.
blue-collar
technician
retired
management
unemployed
self-employed
unknown
entrepreneur
student
Job


Distribution of Marital
count
25000
20000
15000
10000
5000

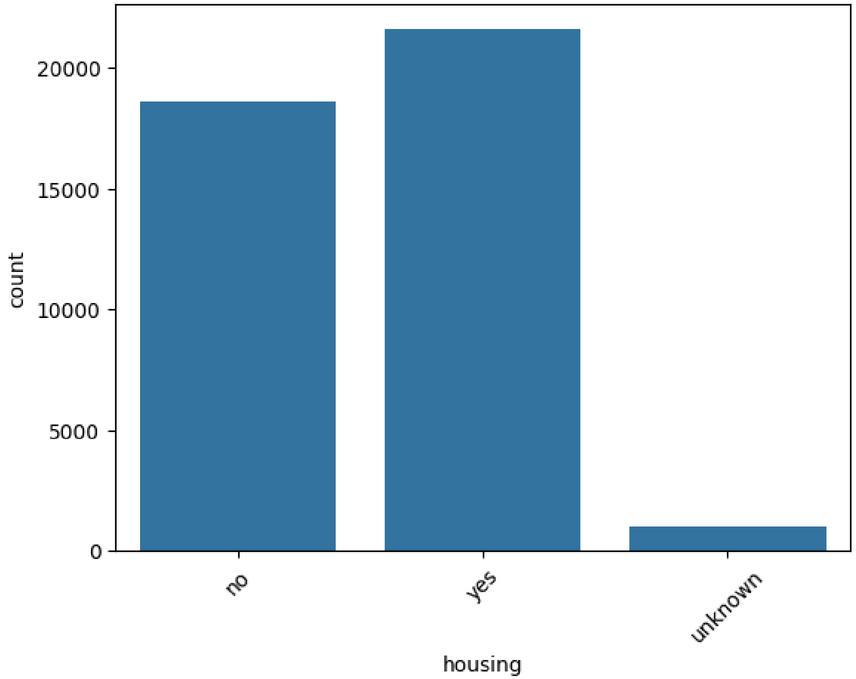

0
married
single
divorced
unknown
Marital


Distribution of Education
count
0
2000
4000
6000
8000
10000
12000
basic.4y
high.school
basic.6y
basic.9y
professional.course
unknown
university.degree
illiterate
Education

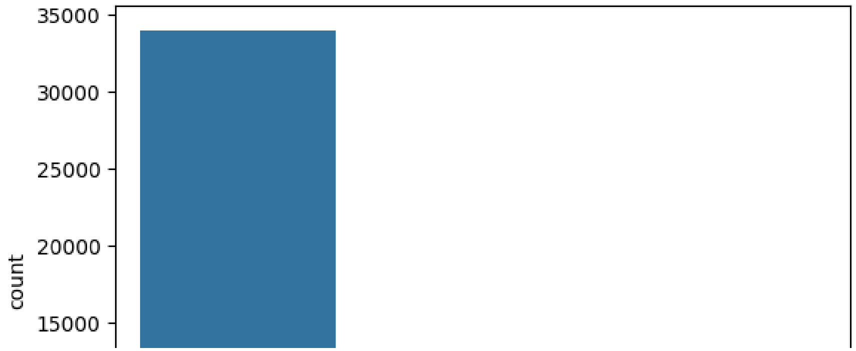

Distribution of Default
count
15000
20000
25000
30000

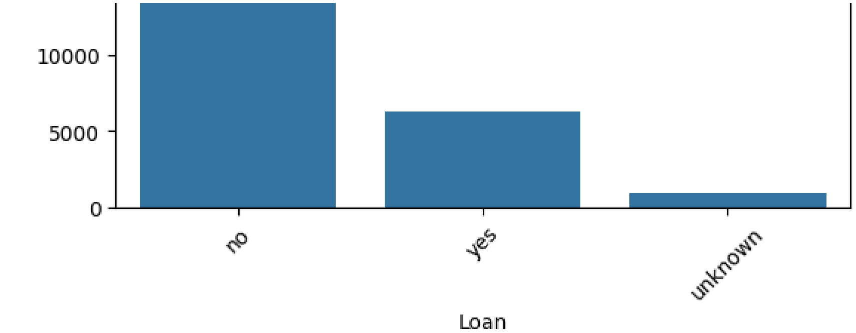


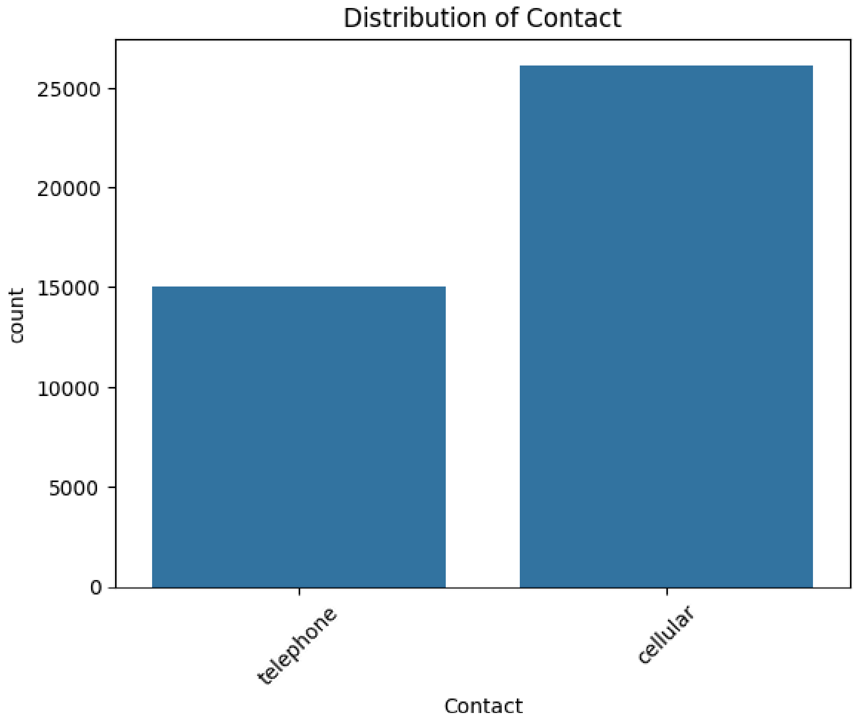

Distribution of housing

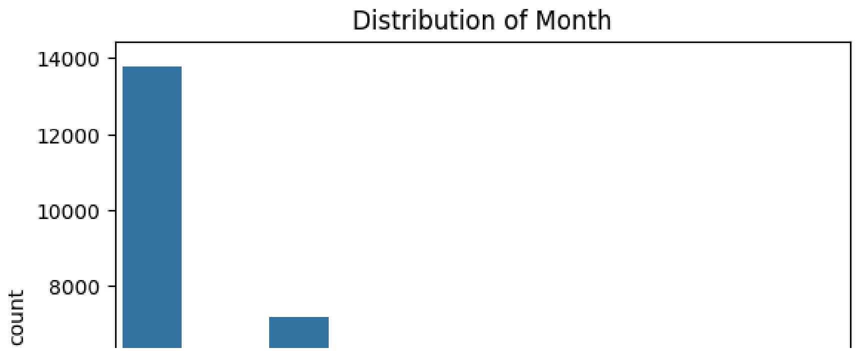


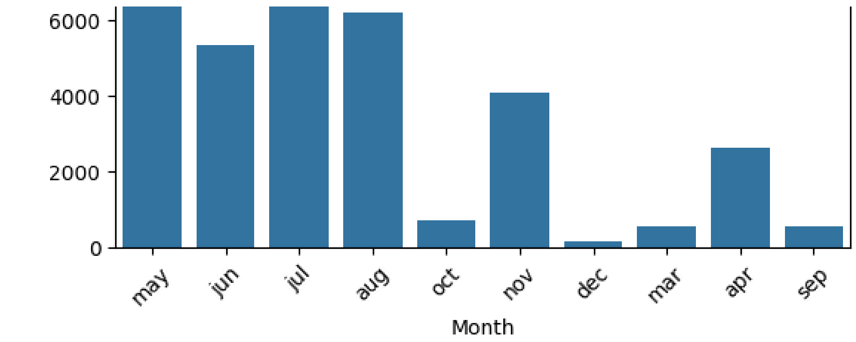

Distribution of Loan



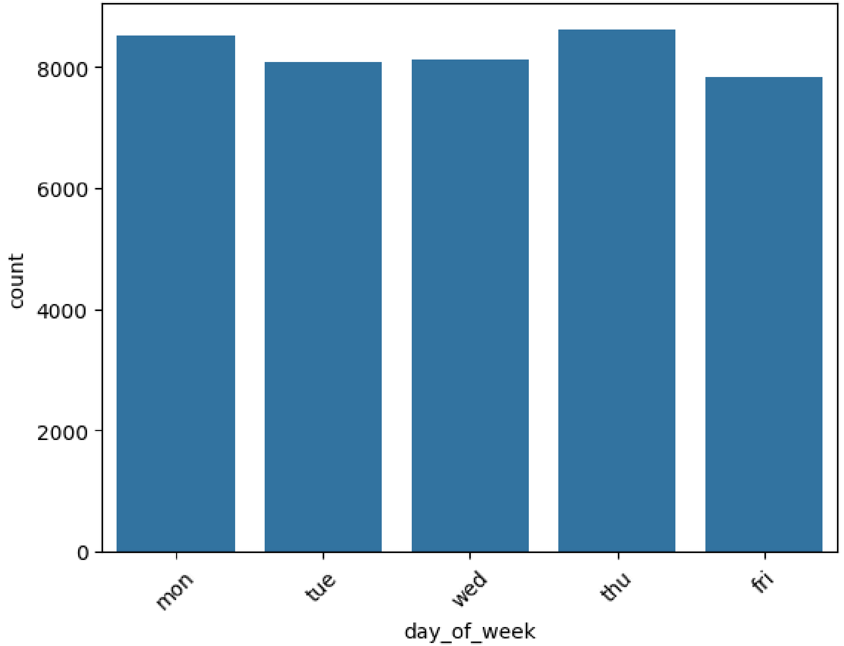

10000
5000
0
no
yes
unknown
Loan


Distribution of Contact
25000
20000
15000
10000
5000
0
count
telephone
cellular
Contact

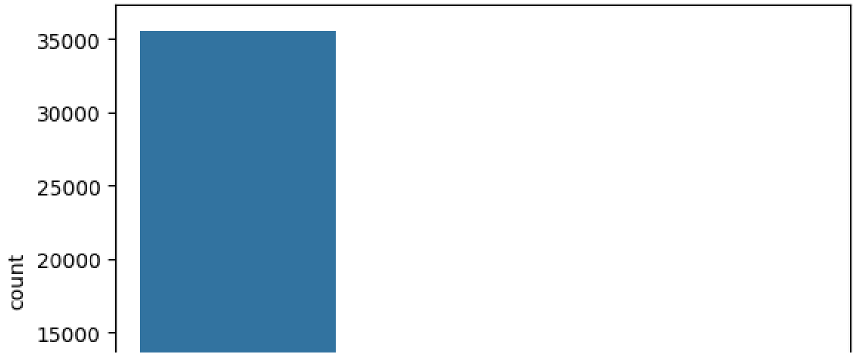

Distribution of Month
14000
12000
10000
8000
count

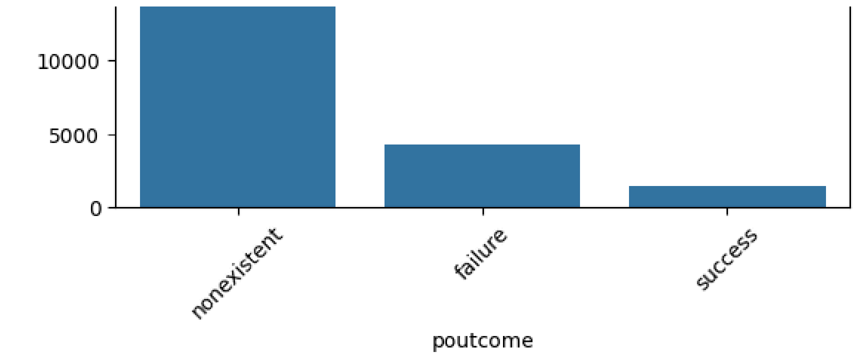


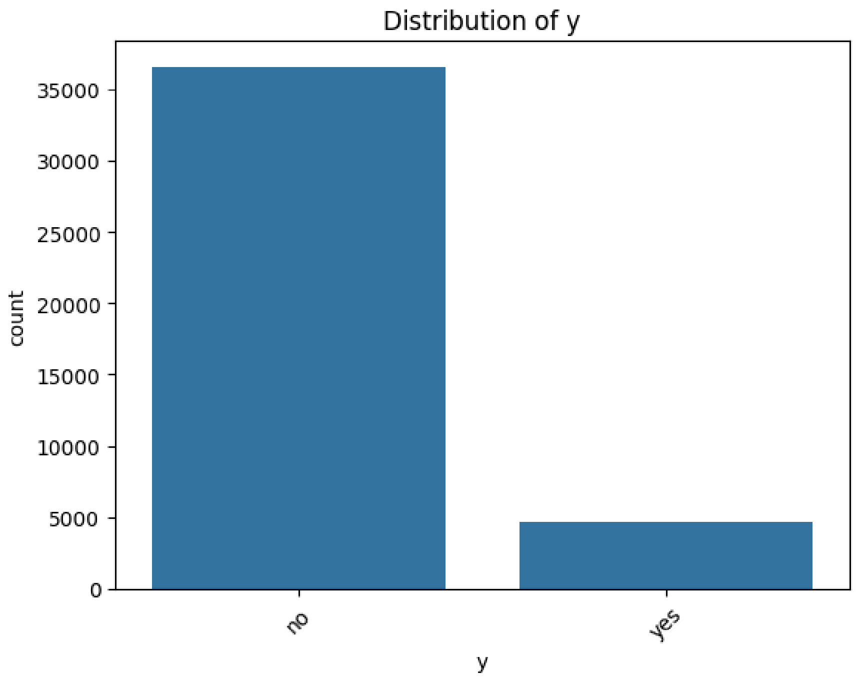

Distribution of day_of_week




Distribution of poutcome






## insights

1.job:-Clients with admin as job type are maximum in the bank and the least are unknown job type clients.Blue-collar job clients take the second place from the top.

2.Marital:- most of clients are married

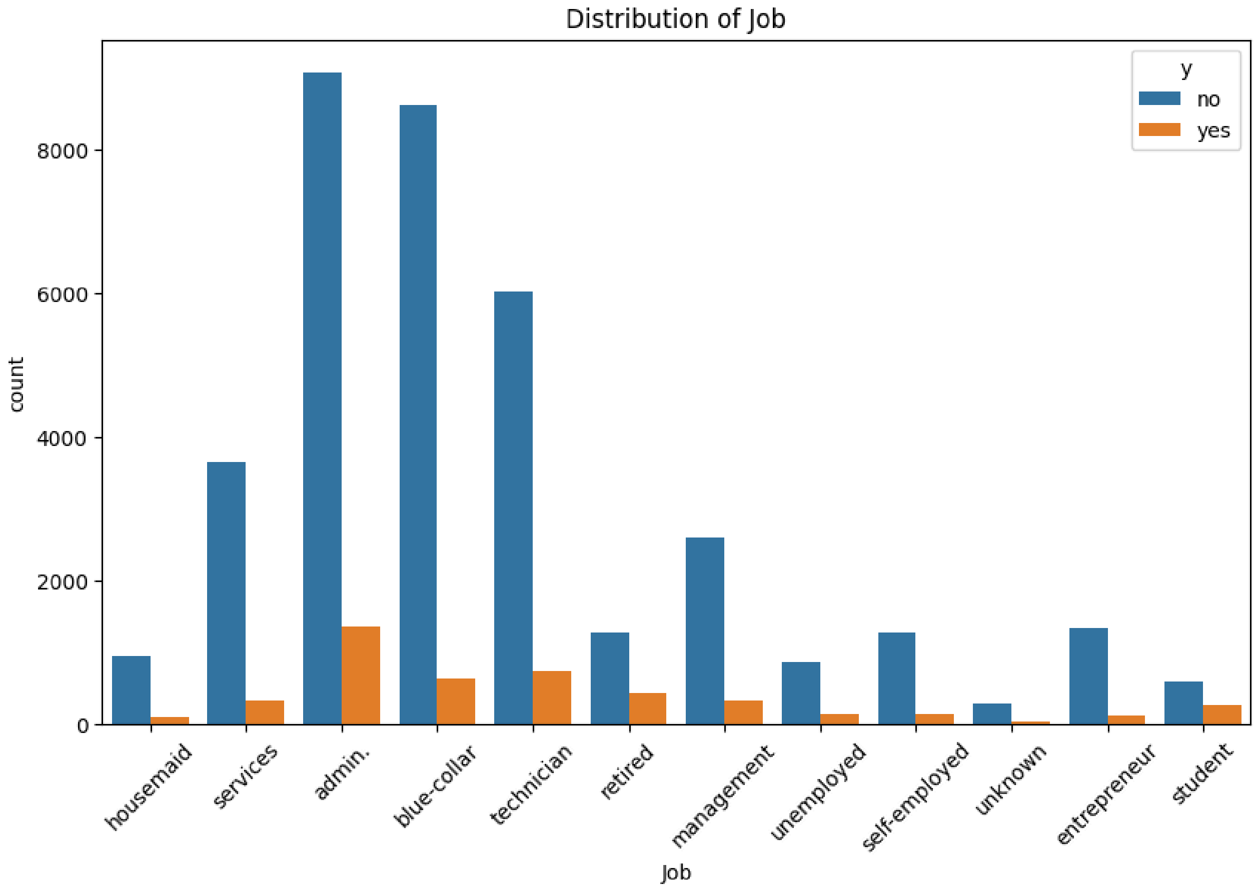
3.Education:- most of clients university graduated

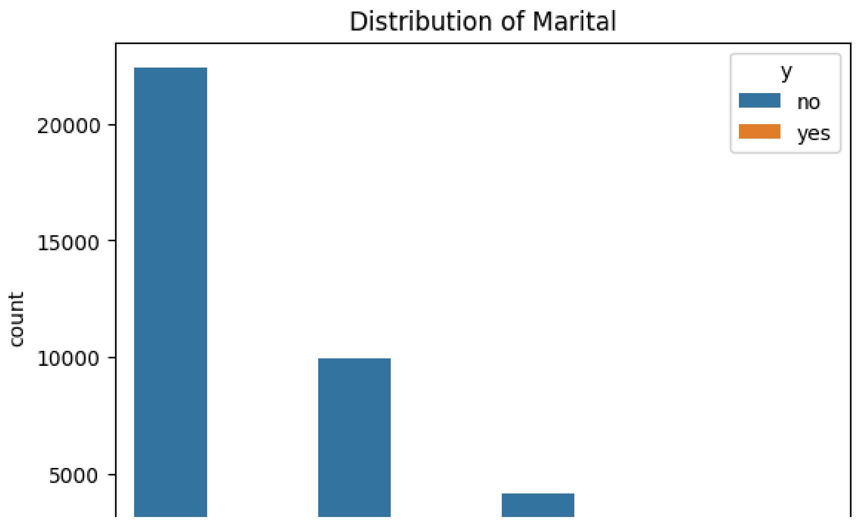
4.houseing:-most of clients have house and some are not

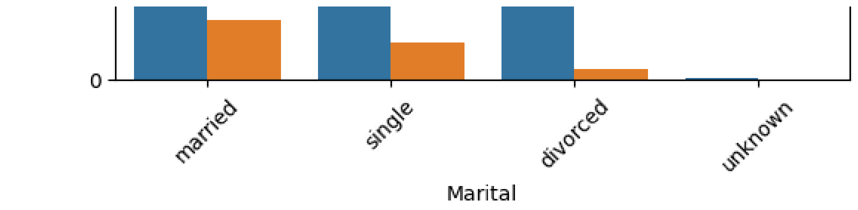
5.loan:-most of clients donts takes any loan

6.month:- most of clients connected May, June, July and August in month

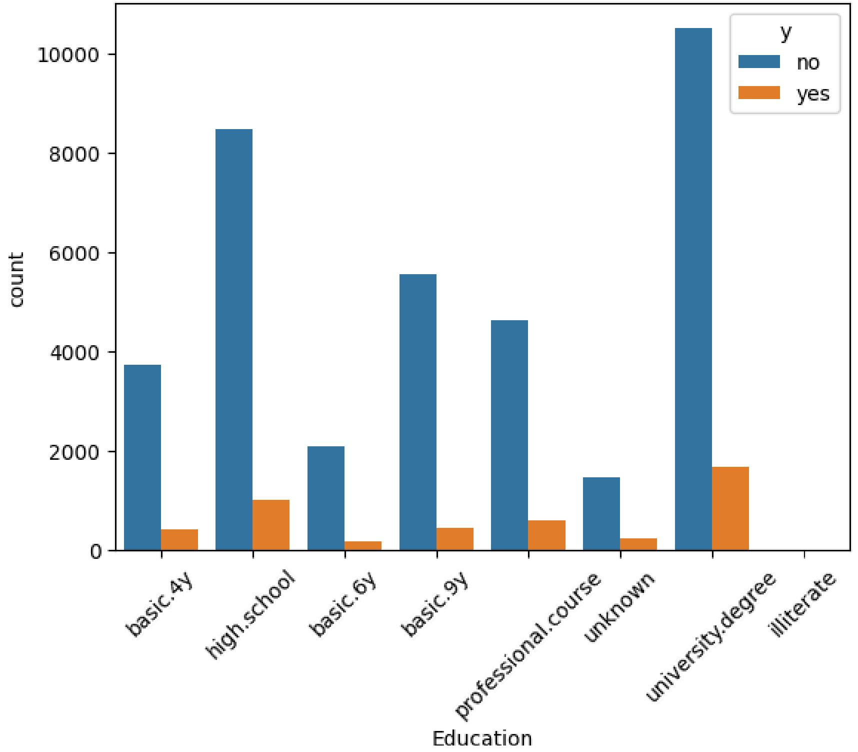
```
# Categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns

plt.figure(figsize=(10,6))
for col in categorical_columns:
    sns.countplot(x=col, data=df,hue='y')
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.show()
```


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

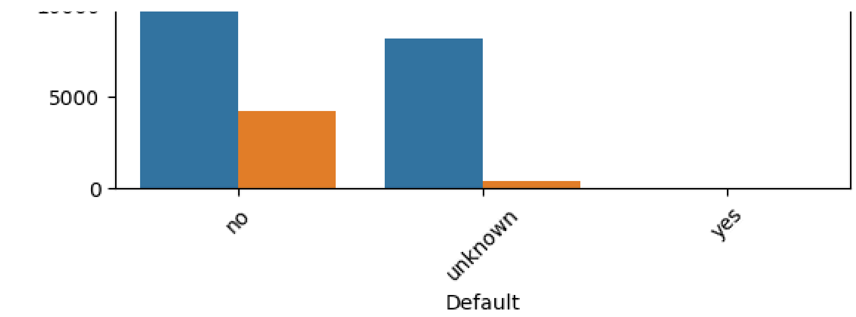

Distribution of Marital
y
no
yes
count
20000
15000
10000
5000

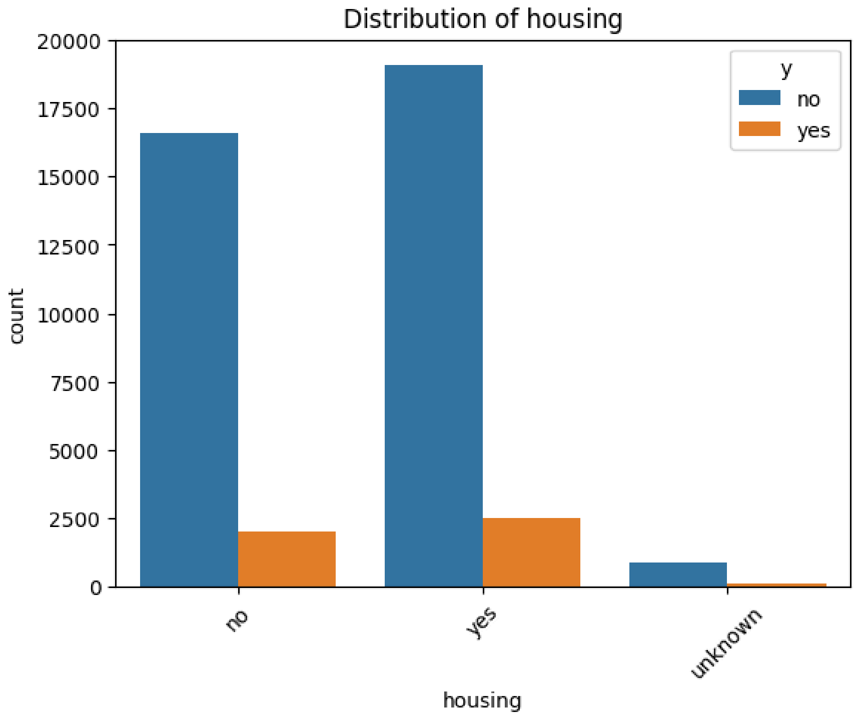


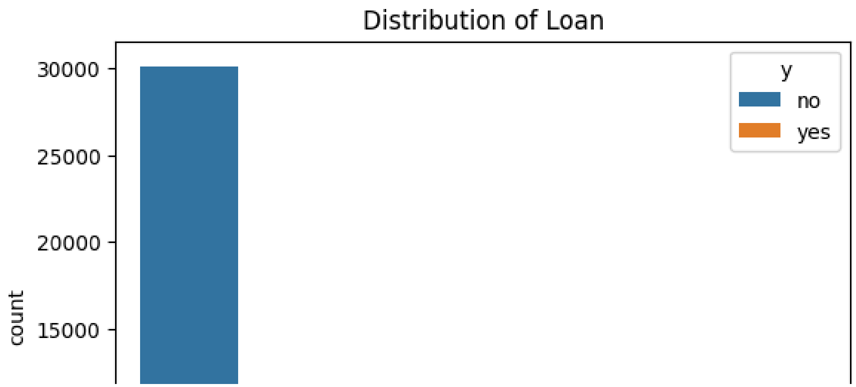

Distribution of Education

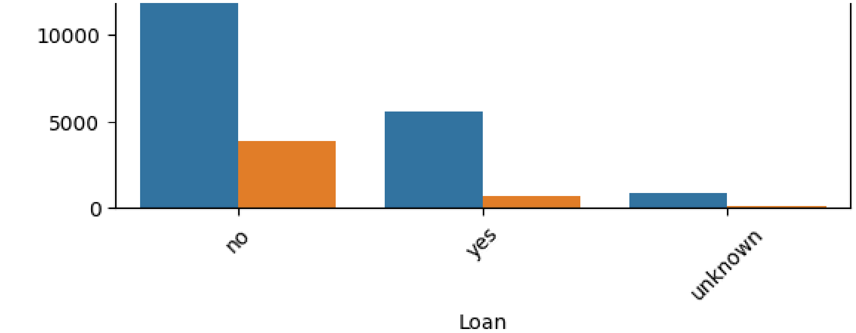


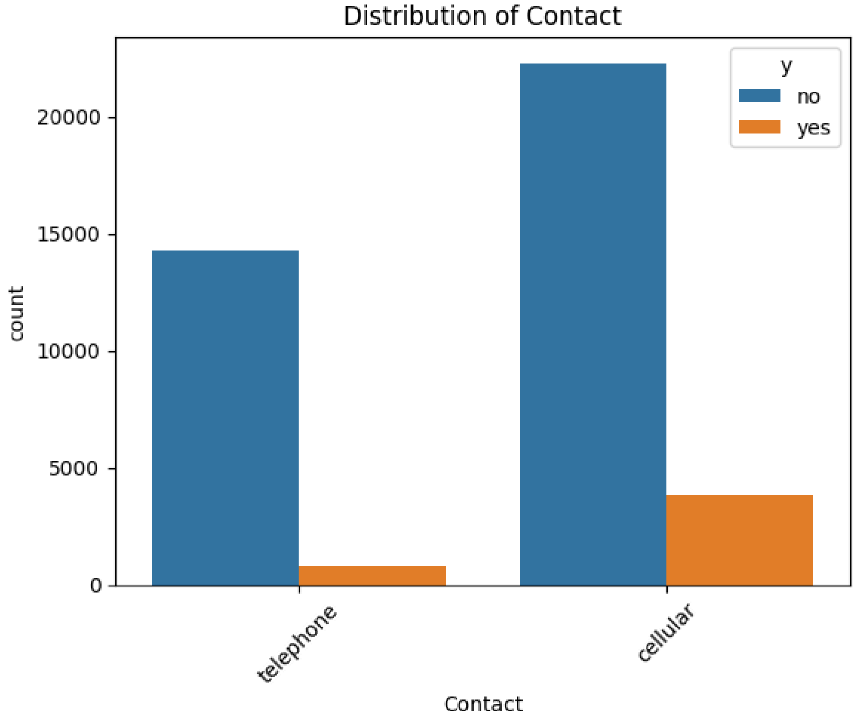

Distribution of Default

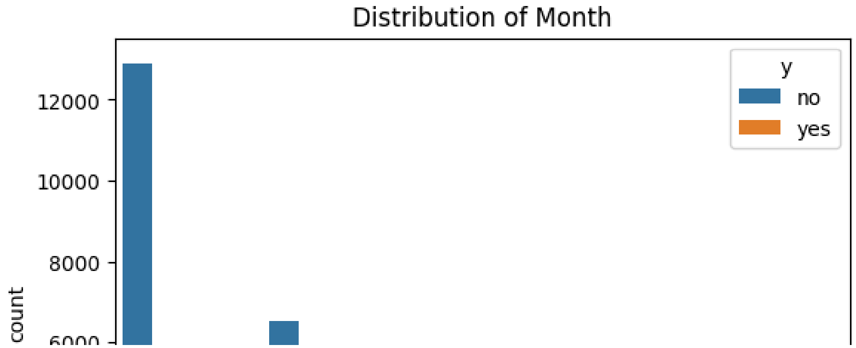

5000
0
no
unknown
yes
Default

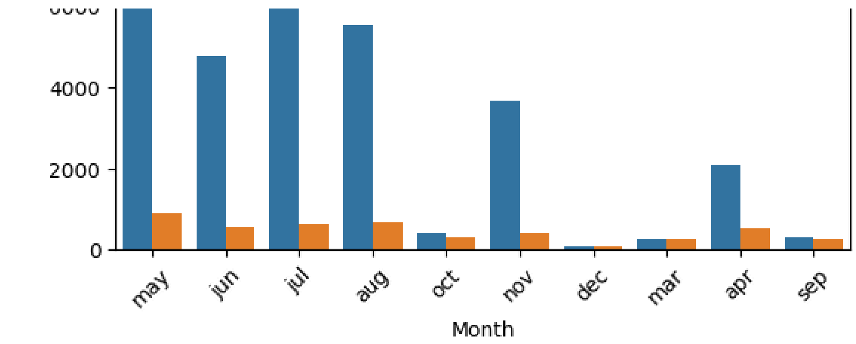

Distribution of housing
20000
17500
15000
12500
10000
7500
5000
2500
0
count
y
no
yes
no
yes
unknown
housing

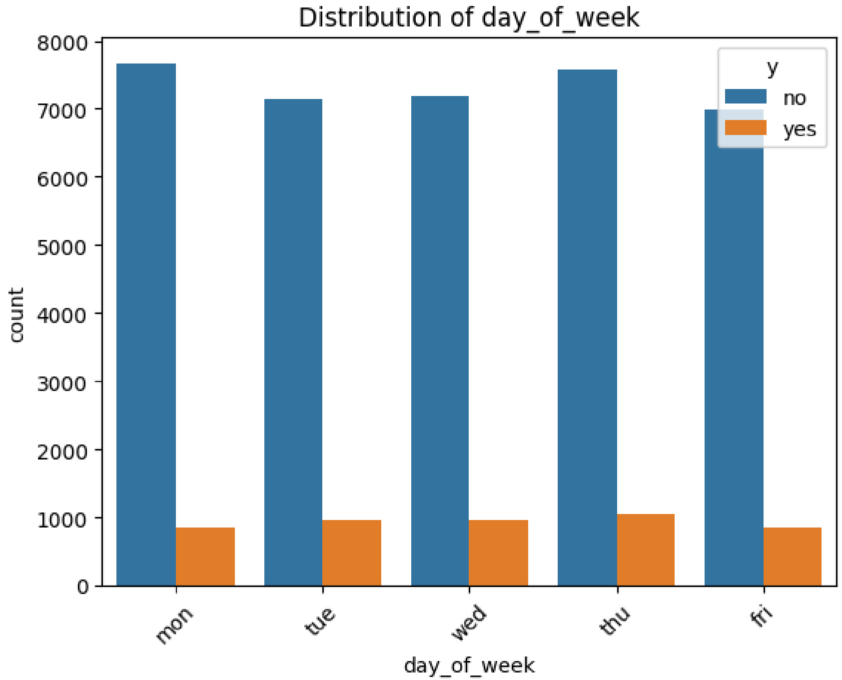

Distribution of Loan
30000
25000
20000
15000
count
y
no
yes

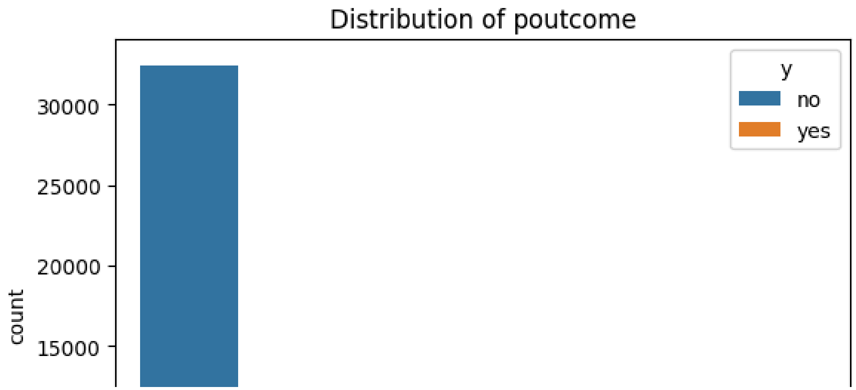

10000
5000
0
no
yes
unknown
Loan

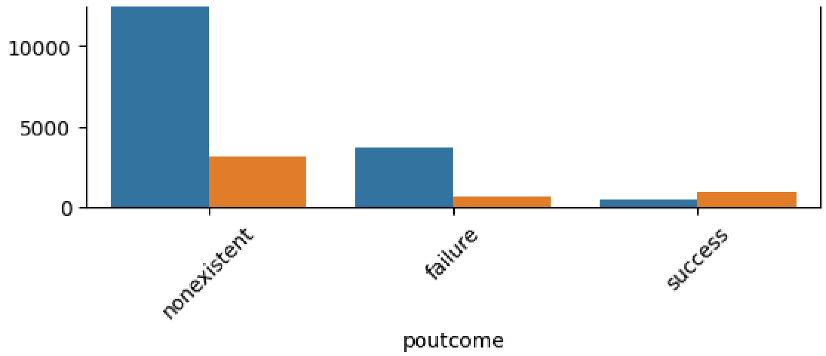

Distribution of Contact
y
no
yes
20000
15000
10000
5000
0
count
telephone
cellular
Contact

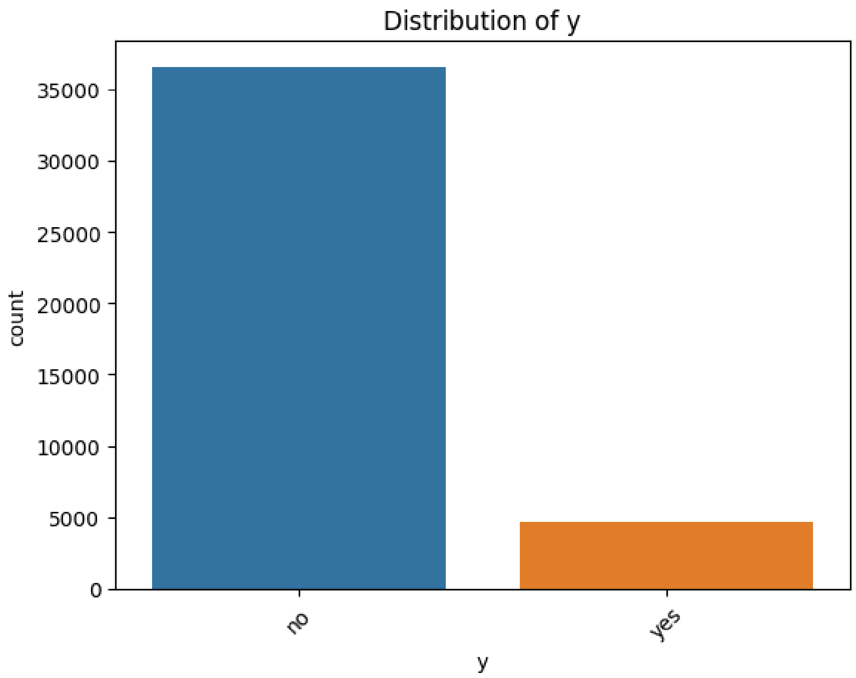

Distribution of Month
y
no
yes
12000
10000
8000
count


4000
2000
0
may
jun
jul
aug
oct
nov
dec
mar
apr
sep
Month


Distribution of day_of_week
8000
7000
6000
5000
4000
3000
2000
1000
0
count
y
no
yes
mon
tue
wed
thu
fri
day_of_week


Distribution of poutcome
30000
25000
20000
15000
count
y
no
yes



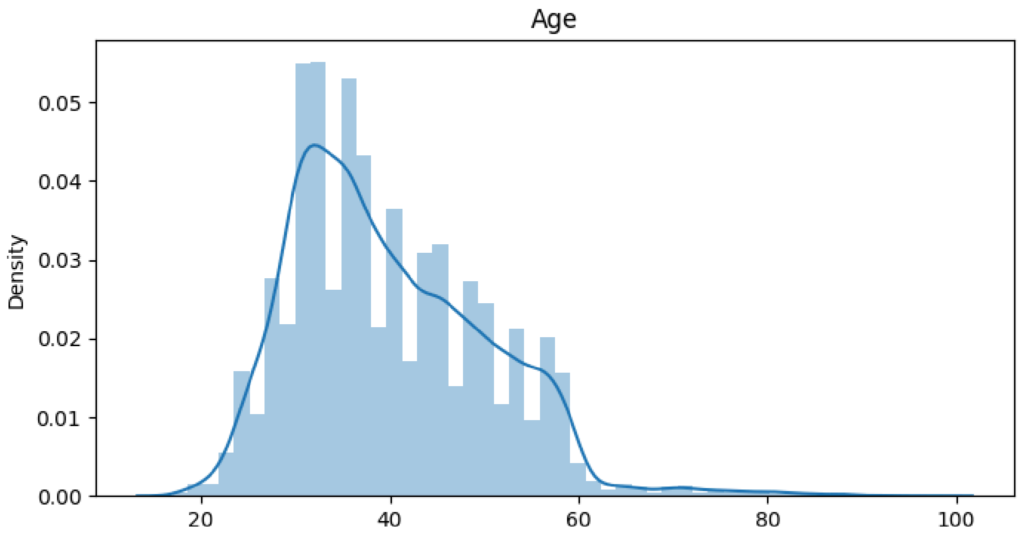



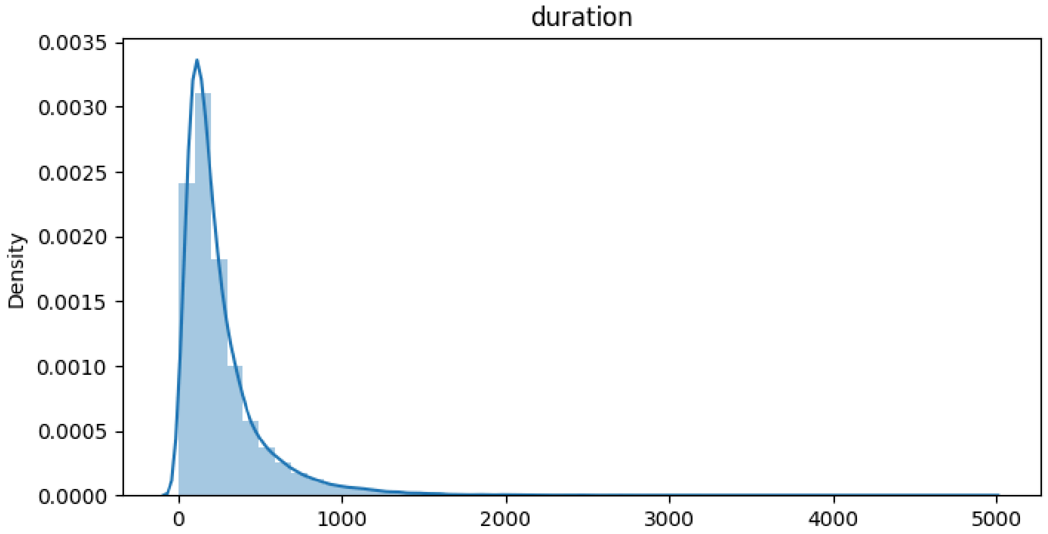

## insights

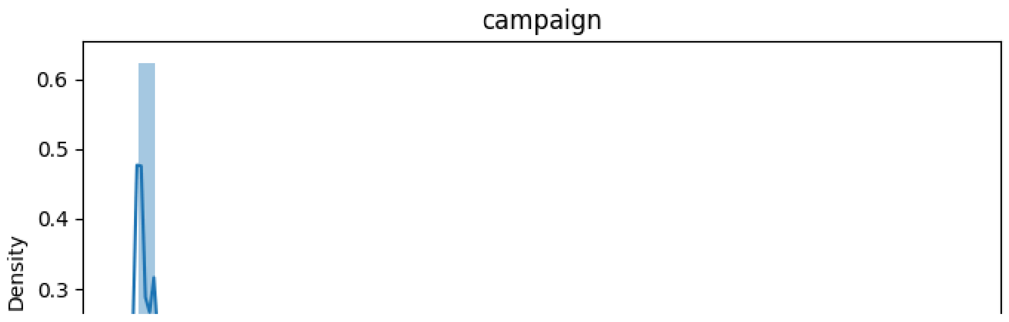
1. job:-Out of all people who have subscribed, admin people have the highest subscriptions followed by other.
2. marital:-Out of all people who have subscribed, married people have the highest subscriptions followed by other two.
3. education:- Out of all students who have subscribed, University people have the highest subscriptions followed by other.
4. housing:- Out of all people who have subscribed, who have own house highest subscriptions followed by other.
5. loan:- Out of all people who have subscribed, who have not taken any loan highest subscriptions followed by other.

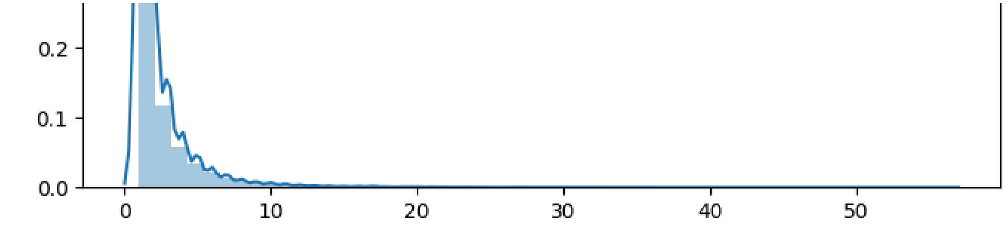
6. Out of all people who have subscribed, may,jun,july and aug have highest subscriptions followed by other month.
7. weekly subscription are good.

```
num_columns = df.select_dtypes(include=['int','float']).columns

for cols in num_columns:
  plt.figure(figsize=(8,4))
  sns.distplot(x=df[cols])
  plt.title(f"{cols}")
  plt.show()
```

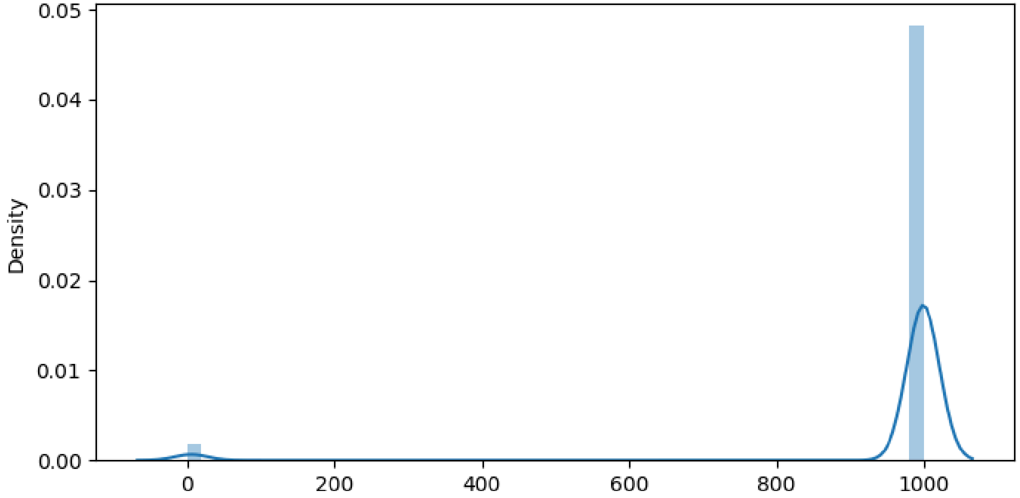

Age
Density
0.00
0.01
0.02
0.03
0.04
0.05
20
40
60
80
100


duration
Density
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0
1000
2000
3000
4000
5000

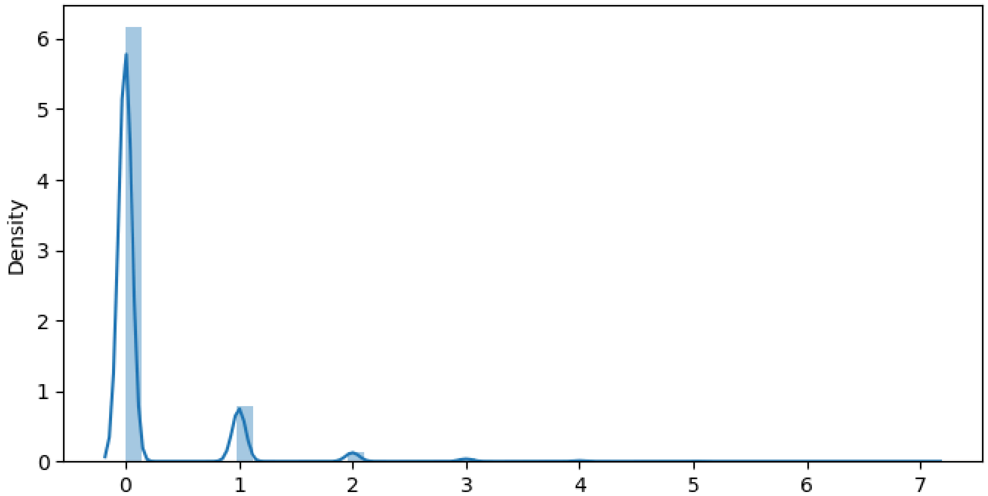

campaign
Density
0.3
0.4
0.5
0.6



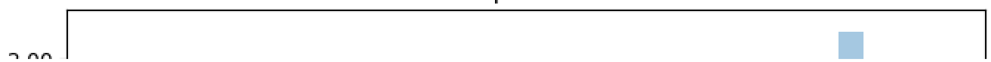

pdays

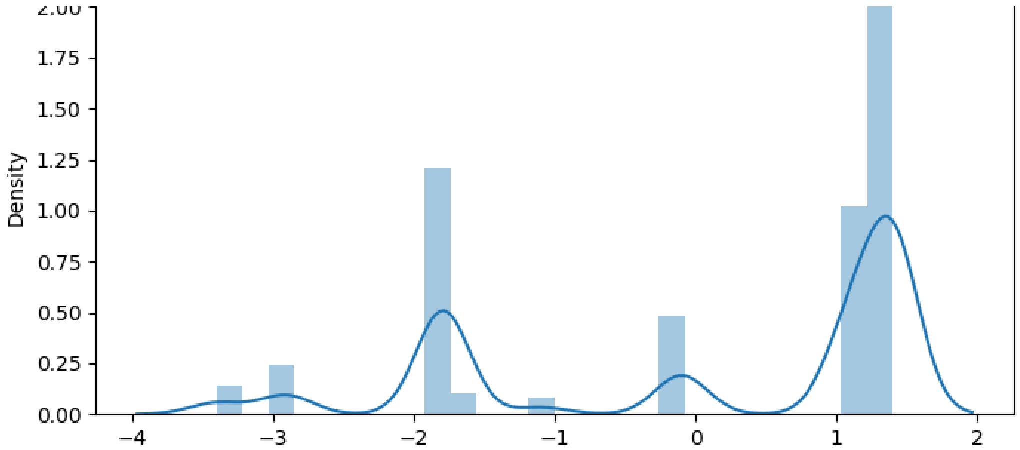



previous

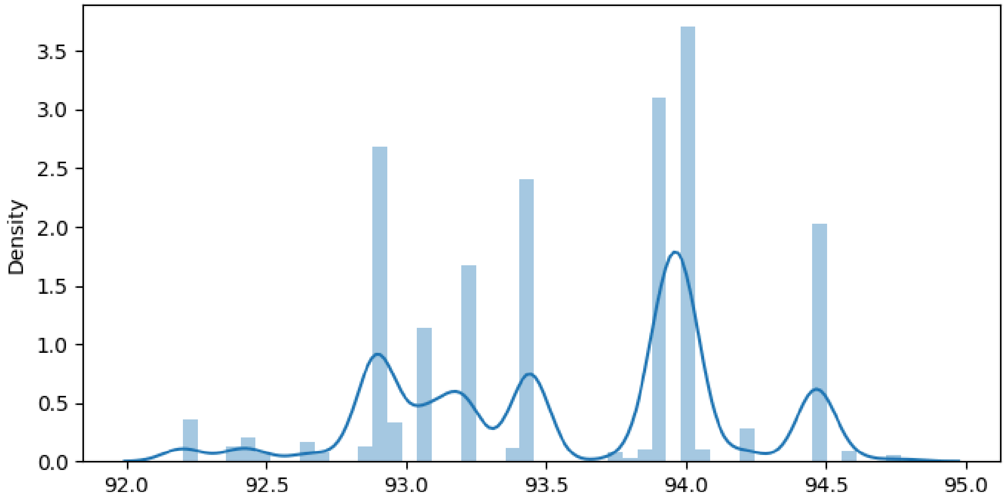



empvarrate

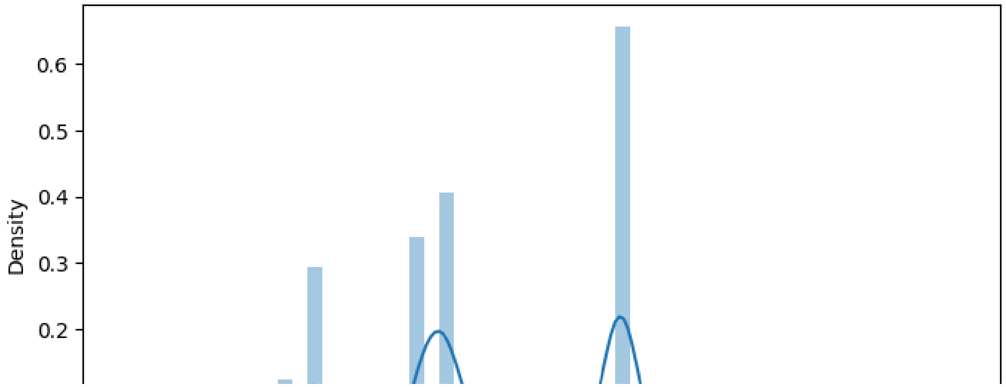


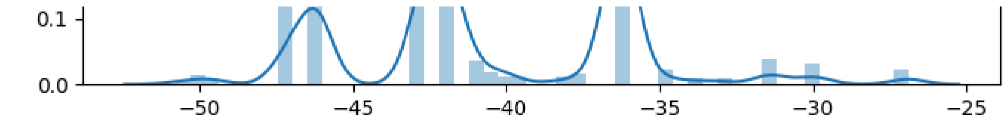



conspriceidx

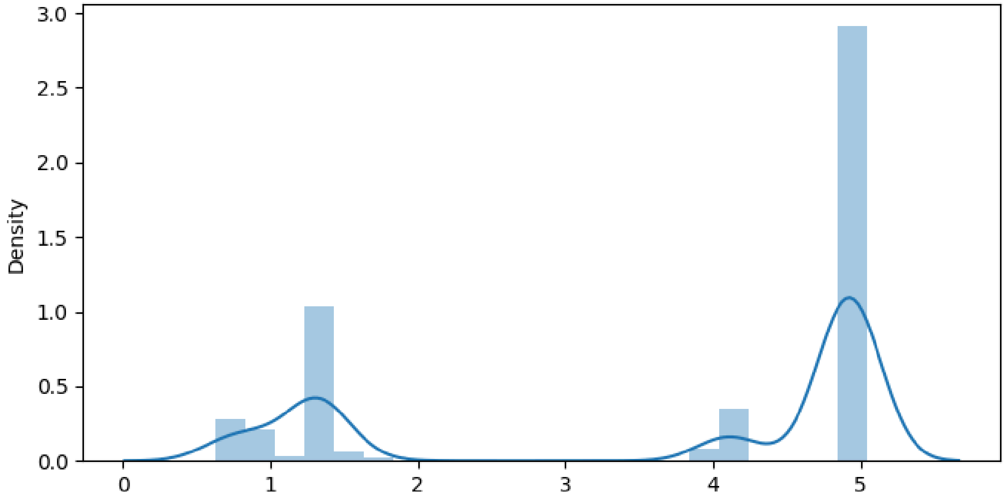



consconfidx

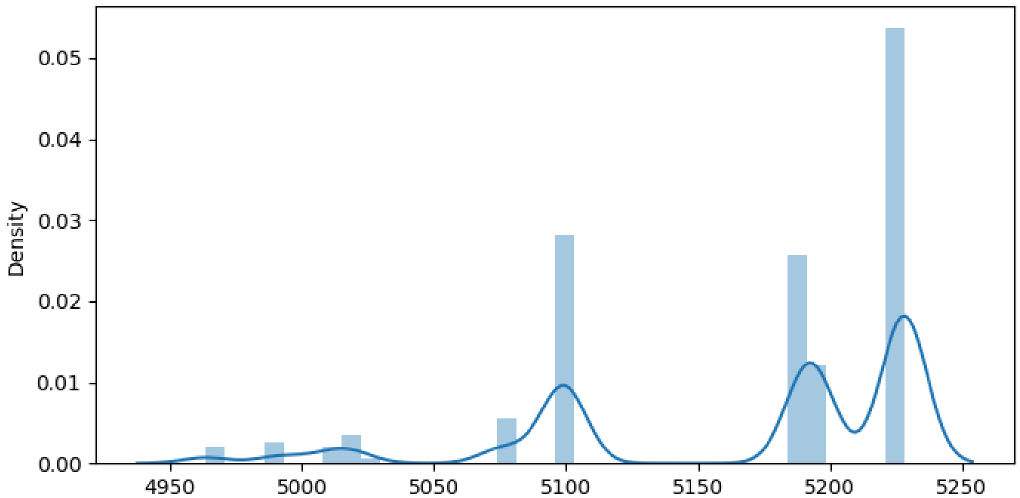




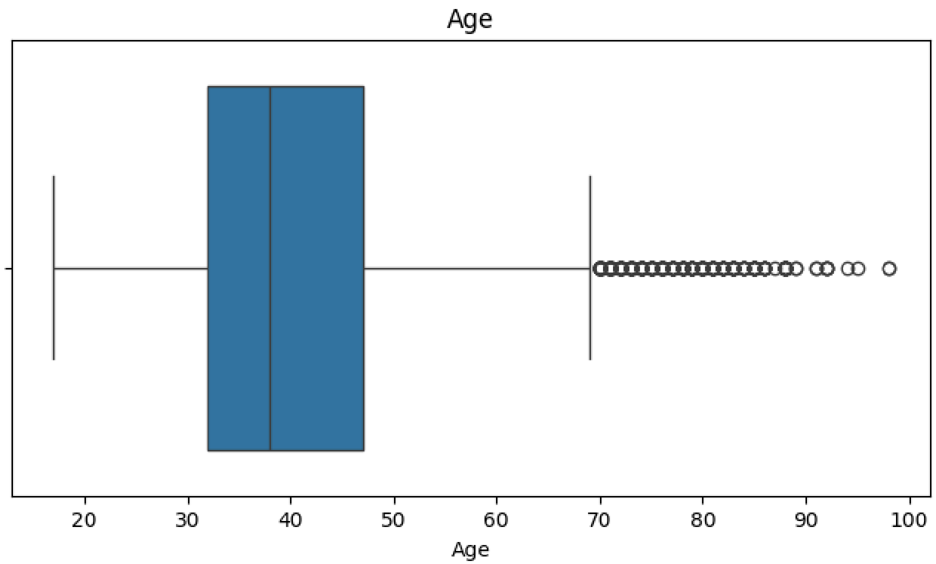

euribor3m

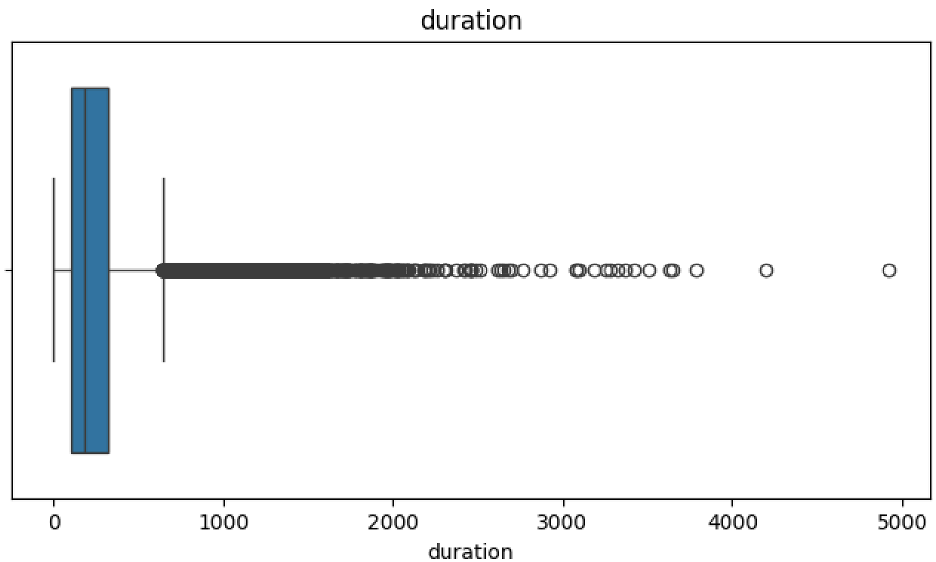


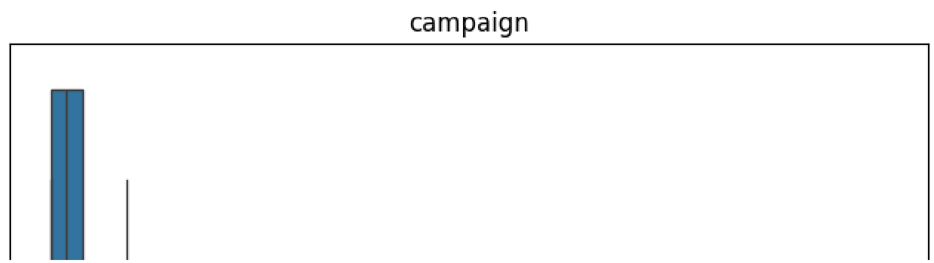

nremployed

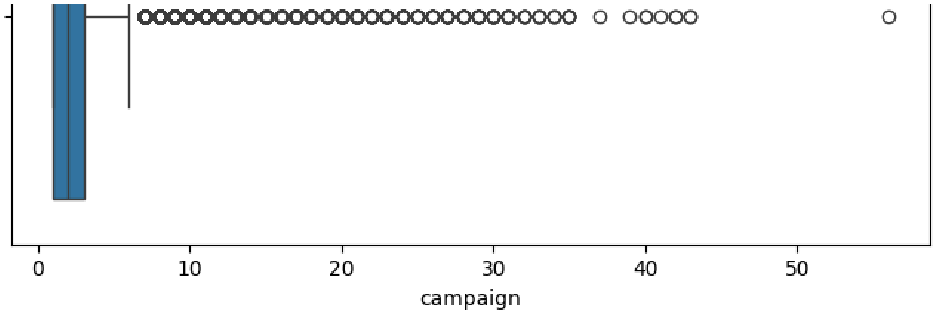


```
num_columns = df.select_dtypes(include=['int','float']).columns

for cols in num_columns:
  plt.figure(figsize=(8,4))
  sns.boxplot(data=df,x=cols)
  plt.title(f"{cols}")
  plt.show()
```

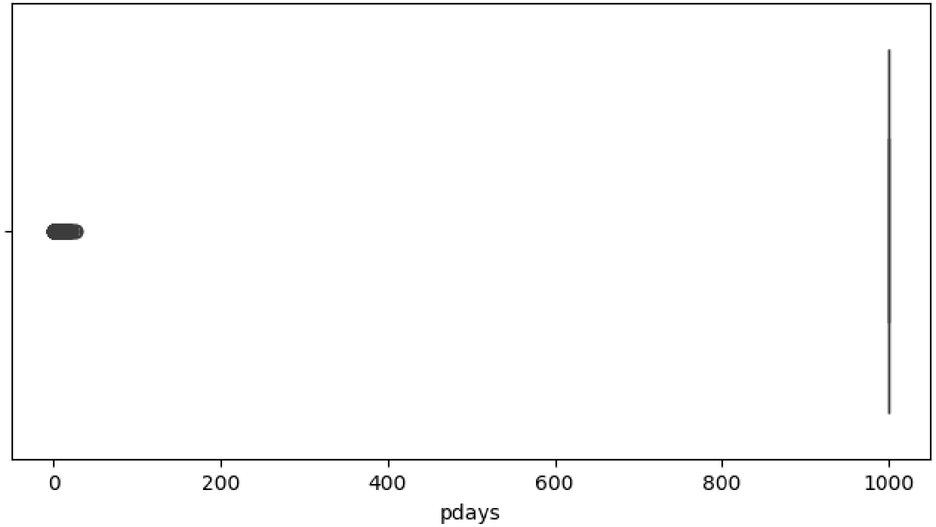

Age
20
30
40
50
60
70
80
90
100
Age


duration
0
1000
2000
3000
4000
5000
duration

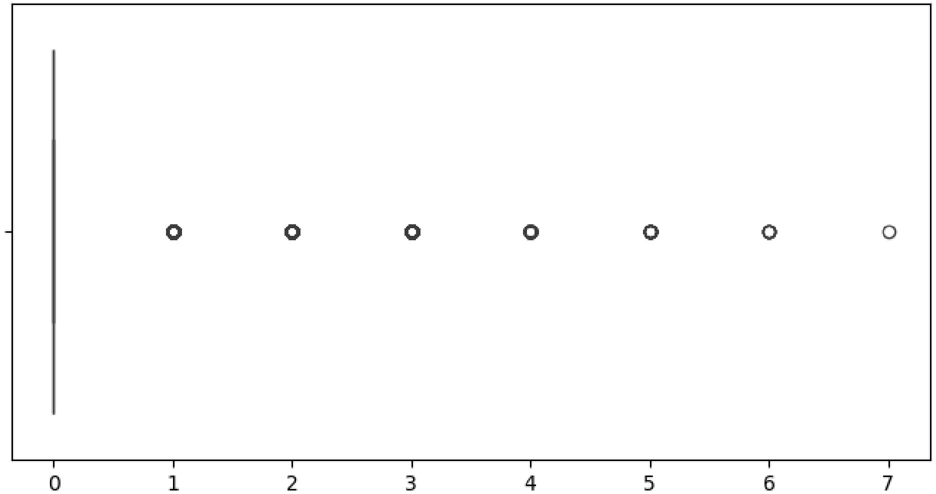

campaign




pdays

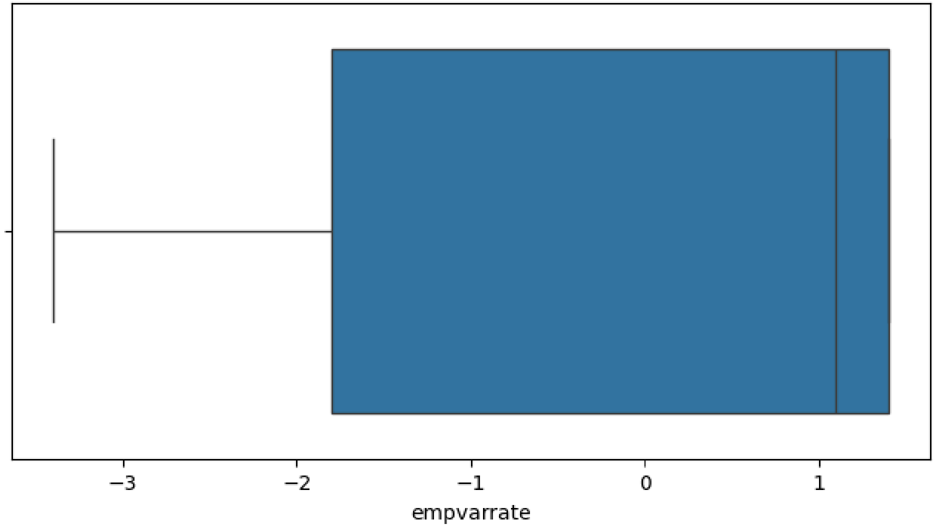



previous

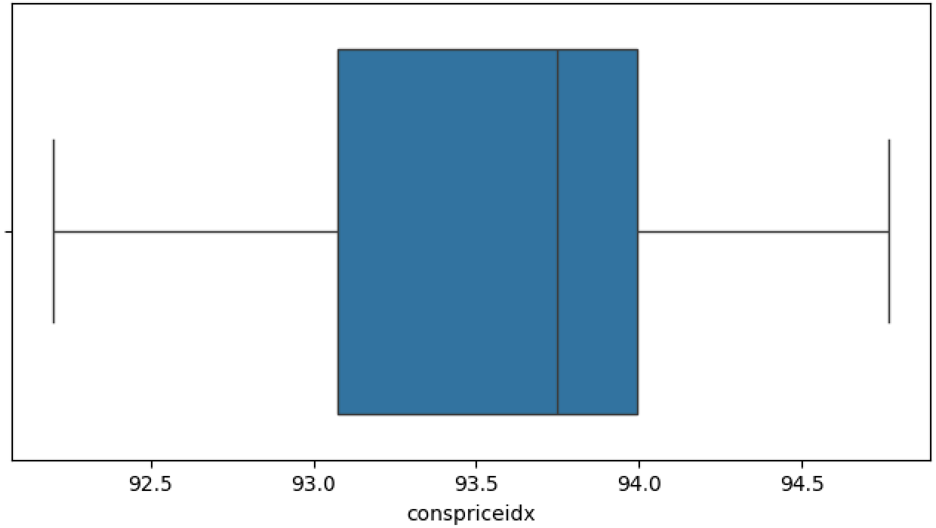


previous

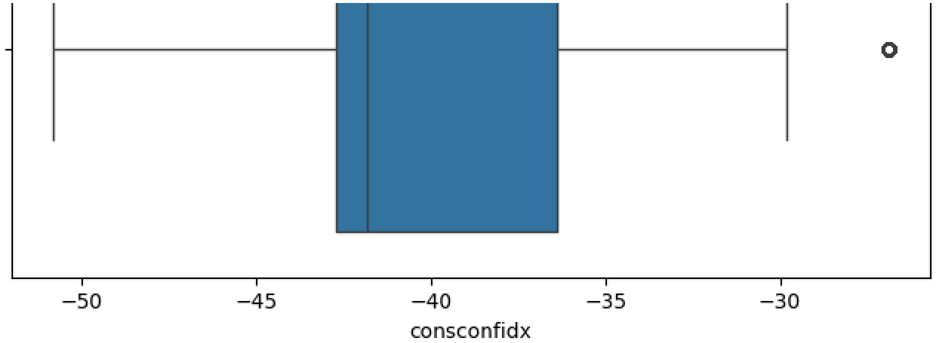
empvarrate



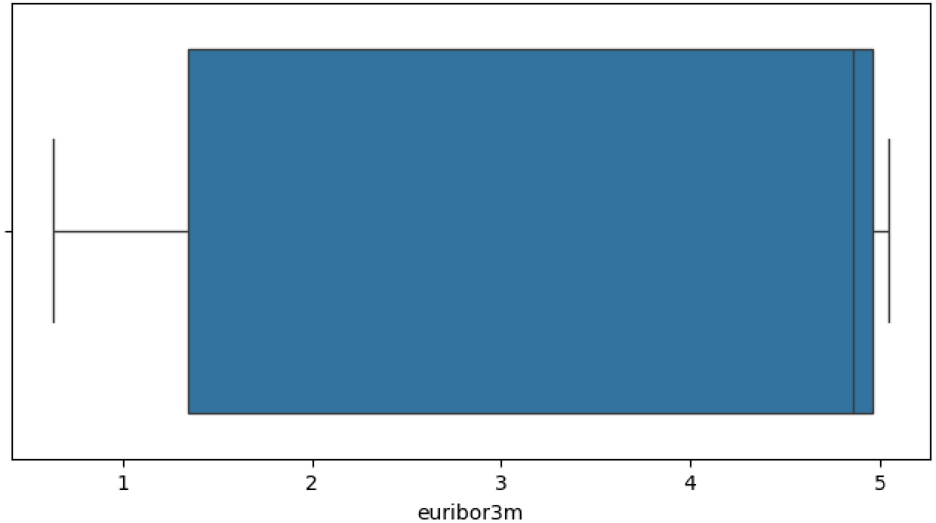

conspriceidx



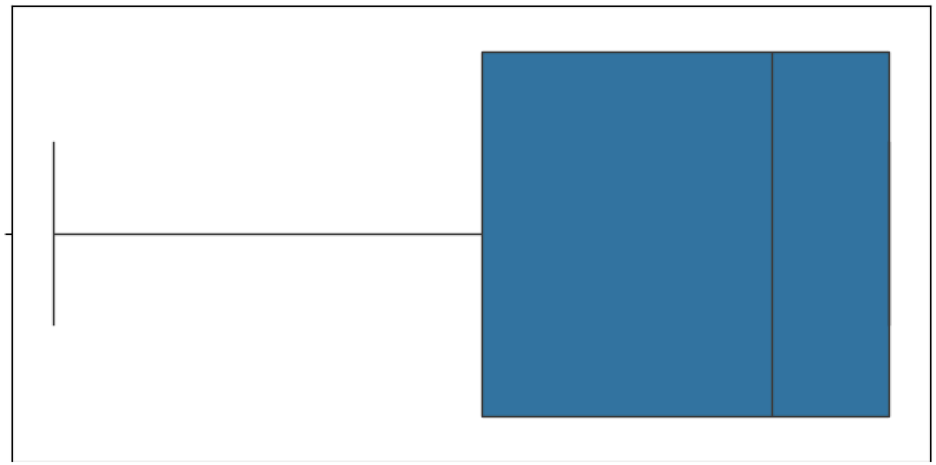

consconfidx

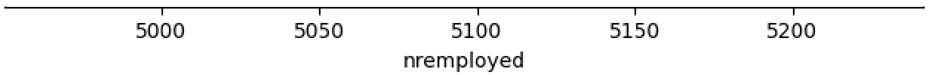



euribor3m




nremployed






## now time i am not remove any outliers if my accuracy not coming good that time,i will be remove outlier

```
df1 = df.copy()
```

## Feature Engineering

```
df1.head(1)
```

| | Age | Job | Marital | Education | Default | housing | Loan | Contact | Month | day_of_week | ... | campaign | pdays | previous | pou |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | housemaid | married | basic.4y | no | no | no | telephone | may | mon | ... | 1 | 999 | 0 | none |

1 rows × 21 columns

```
#df1 = pd.get_dummies(df1,columns=["Job","Marital", "Education", "Default", "day_of_week","Month","poutcome","Contact","housing","Loan"],drop_first=True)
```

```
#from sklearn.preprocessing import LabelEncoder
#df1['y'] = LabelEncoder().fit_transform(df1['y'])
```

```
from sklearn.preprocessing import LabelEncoder

for col in ["Job","Marital", "Education", "Default", "day_of_week","Month","poutcome","Contact","housing","Loan","y"]:
  df1[col] = LabelEncoder().fit_transform(df1[col])
```

```
df1.head()
```

| | Age | Job | Marital | Education | Default | housing | Loan | Contact | Month | day_of_week | ... | campaign | pdays | previous | poutcome | er |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | 3 | 1 | 0 | 0 | 0 | 0 | 1 | 6 | 1 | ... | 1 | 999 | 0 | 1 | |
| **1** | 57 | 7 | 1 | 3 | 1 | 0 | 0 | 1 | 6 | 1 | ... | 1 | 999 | 0 | 1 | |
| **2** | 37 | 7 | 1 | 3 | 0 | 2 | 0 | 1 | 6 | 1 | ... | 1 | 999 | 0 | 1 | |
| **3** | 40 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 6 | 1 | ... | 1 | 999 | 0 | 1 | |
| **4** | 56 | 7 | 1 | 3 | 0 | 0 | 2 | 1 | 6 | 1 | ... | 1 | 999 | 0 | 1 | |

5 rows × 21 columns

## Examine multicollinearity using VIF

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
# VIF dataframe
vif_data = pd.DataFrame()
vif_data['feature']=df1.columns
# calculating VIF for each feature
vif_data['VIF'] = [variance_inflation_factor(df1.values,i) for i in range(len(df1.columns))]
print(vif_data)
```

```
         feature           VIF
0            Age     19.750319
1            Job      2.120020
2        Marital      5.655916
3      Education      4.465785
4        Default      1.405054
5        housing      2.205772
6           Loan      1.207876
7        Contact      2.867920
8          Month      6.844070
9    day_of_week      3.086046
10      duration      2.451816
11      campaign      1.930734
12         pdays    166.324812
13      previous      5.964625
14      poutcome     34.169783
15    empvarrate     40.720000
16  conspriceidx  38875.067588
17   consconfidx    131.865990
18     euribor3m    333.492262
19    nremployed  44294.366566
20             y      1.714541
```

I am dropping the columns based on the results I have gotten from VIF.

```
df1 = df1.drop(['Age','pdays','poutcome','empvarrate','conspriceidx','consconfidx','euribor3m','nremployed'],axis=1)
```

```
df1.head()
```

| | Job | Marital | Education | Default | housing | Loan | Contact | Month | day_of_week | duration | campaign | previous | y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | 1 | 0 | 0 | 0 | 0 | 1 | 6 | 1 | 261 | 1 | 0 | 0 |
| **1** | 7 | 1 | 3 | 1 | 0 | 0 | 1 | 6 | 1 | 149 | 1 | 0 | 0 |
| **2** | 7 | 1 | 3 | 0 | 2 | 0 | 1 | 6 | 1 | 226 | 1 | 0 | 0 |
| **3** | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 6 | 1 | 151 | 1 | 0 | 0 |
| **4** | 7 | 1 | 3 | 0 | 0 | 2 | 1 | 6 | 1 | 307 | 1 | 0 | 0 |

## Split Data Into Train and Test

```
from sklearn.model_selection import train_test_split
x = df1.drop(['y'],axis=1)
y = df1['y']
x_train,x_test,y_train,y_test = train_test_split(x, y, test_size=0.3, random_state=42)
print(x_train.shape)
print(x_test.shape)
```

```
(28823, 12)
(12353, 12)
```

## Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_train
```

```
array([[-0.47664322, -0.28333937, -0.81764805, ..., -0.22109932,
         0.51918344, -0.34718659],
       [-0.75476873, -0.28333937, -0.81764805, ...,  6.55526628,
        -0.57249939, -0.34718659],
       [-1.03289423,  1.35820651,  1.05621203, ..., -0.8381844 ,
        -0.57249939, -0.34718659],
       ...,
       [ 0.3577333 , -0.28333937, -1.75457809, ..., -0.02826023,
        -0.20860511,  3.70749702],
       [ 0.07960779, -0.28333937,  1.05621203, ...,  0.14529495,
        -0.20860511, -0.34718659],
```

```
       [ 1.19210982,  1.35820651, -0.81764805, ..., -0.65691566,
         0.51918344, -0.34718659]])
```

```
x_test = sc.transform(x_test)
x_test
```

```
     array([[ 0.3577333 , -0.28333937,  0.58774701, ...,  4.63844573,
             -0.57249939, -0.34718659],
            [-0.75476873, -0.28333937, -0.81764805, ..., -0.03597379,
             -0.57249939,  1.68015521],
            [ 1.47023533, -0.28333937,  0.58774701, ...,  0.06815931,
             -0.20860511, -0.34718659],
            ...,
            [-1.03289423,  1.35820651,  1.05621203, ..., -0.07839839,
             -0.20860511, -0.34718659],
            [-1.03289423, -0.28333937,  1.05621203, ..., -0.46021979,
             -0.20860511, -0.34718659],
            [-0.75476873, -0.28333937, -0.81764805, ..., -0.96160142,
              1.24697199, -0.34718659]])
```

```
from sklearn.metrics import accuracy_score, log_loss
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.metrics import accuracy_score , classification_report, ConfusionMatrixDisplay,precision_score,recall_score, f1_score,roc_auc_score,roc_curve
```

```
df1['y'].value_counts()
```

```
     0    36537
     1     4639
     Name: y, dtype: int64
```

## above we can our data imbalanced

```
from imblearn.over_sampling import SMOTE
smote = SMOTE()
x_smote,y_smote = smote.fit_resample(x, y)
```

```
y_smote.value_counts()
```

```
     0    36537
     1    36537
     Name: y, dtype: int64
```

```
x_train,x_test,y_train,y_test = train_test_split(x_smote, y_smote, test_size=0.3, random_state=42)
```

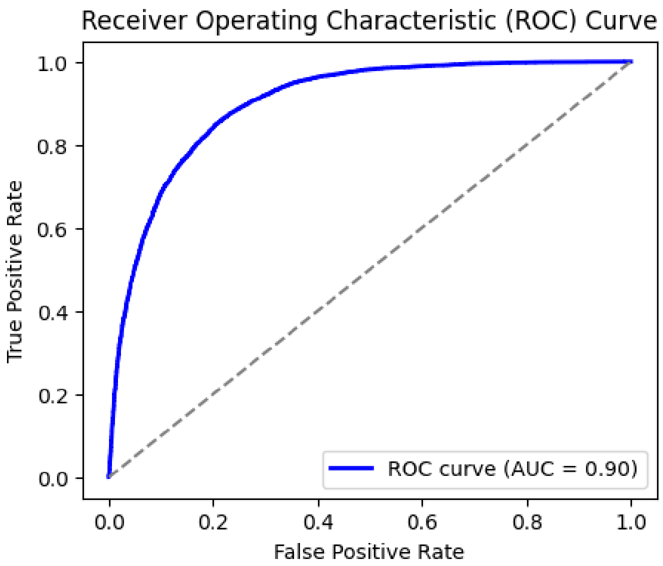
```
lr = LogisticRegression()
lr.fit(x_train,y_train)
lr.score(x_train,y_train)
```

```
0.8218021153056636
```

```
lr_pred = lr.predict(x_test)

accuracy = accuracy_score(y_test,lr_pred)
clf_report = classification_report(y_test,lr_pred)
print("logistic regression")
print(f"accuracy:", accuracy)
print(clf_report)
```

```
logistic regression
accuracy: 0.8193677872553938
              precision    recall  f1-score   support

           0       0.83      0.81      0.82     11029
           1       0.81      0.83      0.82     10894

    accuracy                           0.82     21923
   macro avg       0.82      0.82      0.82     21923
weighted avg       0.82      0.82      0.82     21923
```

```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Calculate predicted probabilities
y_scores = lr.predict_proba(x_test)[:, 1]

# Calculate ROC curve
fpr, tpr, _ = roc_curve(y_test, y_scores)

# Calculate AUC
roc_auc = roc_auc_score(y_test, y_scores)

# Plot ROC curve
plt.figure(figsize=(5, 4))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```




## random Forest

```
rand = RandomForestClassifier()
rand.fit(x_train,y_train)
rand.score(x_train,y_train)
```

```
0.9999022502003871
```

```
rand_pred = rand.predict(x_test)

accuracy = accuracy_score(y_test,rand_pred)
clf_report = classification_report(y_test,rand_pred)
print("random forest")
print(f"accuracy:", accuracy)
print(clf_report)
```

```
random forest
accuracy: 0.920950599826666
              precision    recall  f1-score   support

           0       0.94      0.90      0.92     11029
           1       0.90      0.94      0.92     10894

    accuracy                           0.92     21923
   macro avg       0.92      0.92      0.92     21923
weighted avg       0.92      0.92      0.92     21923
```

## decision Tree

```
d_tree = DecisionTreeClassifier()
d_tree.fit(x_train,y_train)
d_tree.score(x_train,y_train)
```

```
0.9999022502003871
```

```
d_tree_pred = d_tree.predict(x_test)
```