## Importing sufficient Libararies

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
df=pd.read_csv('/content/Bank Marketing.csv')
df
```

	Age	Job	Marital Status	Education Cr		Balance (euros)	Housing Loan	Personal Loan	Contact	L Cont
0	58	management	married	tertiary	no	2143	yes	no	unknown	
1	44	technician	single	secondary	no	29	yes	no	unknown	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	
4	33	unknown	single	unknown	no	1	no	no	unknown	
45206	51	technician	married	tertiary	no	825	no	no	cellular	
45207	71	retired	divorced	primary	no	1729	no	no	cellular	
45208	72	retired	married	secondary	no	5715	no	no	cellular	
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	

45211 rows × 17 columns



```
#Number of Rows and columns
df.shape
```

(45211, 17)

```
#first 5 observation print
df.head()
```

	Age	Job	Marital Status	Education	Credit	Balance (euros)	Housing Loan	Personal Loan	Contact	Last Contact Day
0	58	management	married	tertiary	no	2143	yes	no	unknown	5
1	44	technician	single	secondary	no	29	yes	no	unknown	5
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5

#last 5 observation print
df.tail()

	Age	Job Marita Statu		Education	Credit	Credit Balance I (euros)		Personal Loan	Contact	L: Cont
45206	51	technician	married	tertiary	no	825	no	no	cellular	
45207	71	retired	divorced	primary	no	1729	no	no	cellular	
45208	72	retired	married	secondary	no	5715	no	no	cellular	
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	



#Column Heading print df.columns

#Each column types
df.dtypes

Age Job	int64 object
Marital Status	object
Education	object
Credit	object
Balance (euros)	int64
Housing Loan	object
Personal Loan	object
Contact	object
Last Contact Day	int64
Last Contact Month	object
Last Contact Duration	int64
Campaign	int64
Pdays	int64
Previous	int64
Poutcome	object

Subscription int64 dtype: object

# #Information on features 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 Status	45211 non-null	object
3	Education	45211 non-null	object
4	Credit	45211 non-null	object
5	Balance (euros)	45211 non-null	int64
6	Housing Loan	45211 non-null	object
7	Personal Loan	45211 non-null	object
8	Contact	45211 non-null	object
9	Last Contact Day	45211 non-null	int64
10	Last Contact Month	45211 non-null	object
11	Last Contact 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	Subscription	45211 non-null	int64
44	:-+<4/0\ - +/0\		

dtypes: int64(8), object(9)
memory usage: 5.9+ MB

# #Mathematical Correlation df.describe()

	Age	Balance (euros)	Last Contact Day	Last Contact Duration	Campaign	Pdays	Pr
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0

#To find Missing values
df.isna().sum()

Age	0
Job	0
Marital Status	0
Education	0
Credit	0
Balance (euros)	0

```
Housing Loan
                         0
Personal Loan
Contact
                         0
Last Contact Day
                         0
Last Contact Month
Last Contact Duration
                         0
Campaign
                         0
Pdays
                         0
                         0
Previous
                         0
Poutcome
                         0
Subscription
dtype: int64
```

#### **Each string column Unique Values**

```
df['Job'].unique()
    array(['management', 'technician', 'entrepreneur', 'blue-collar',
            'unknown', 'retired', 'admin.', 'services', 'self-employed',
            'unemployed', 'housemaid', 'student'], dtype=object)
df['Marital Status'].unique()
    array(['married', 'single', 'divorced'], dtype=object)
df['Education'].unique()
    array(['tertiary', 'secondary', 'unknown', 'primary'], dtype=object)
df['Credit'].unique()
    array(['no', 'yes'], dtype=object)
df['Housing Loan'].unique()
    array(['yes', 'no'], dtype=object)
df['Personal Loan'].unique()
    array(['no', 'yes'], dtype=object)
df['Contact'].unique()
    array(['unknown', 'cellular', 'telephone'], dtype=object)
df['Last Contact Month'].unique()
    array(['may', 'jun', 'jul', 'aug', 'oct', 'nov', 'dec', 'jan', 'feb',
           'mar', 'apr', 'sep'], dtype=object)
df['Poutcome'].unique()
    array(['unknown', 'failure', 'other', 'success'], dtype=object)
```

#### TARGET COLUMN VALUE COUNTS, GRAPH PLOT

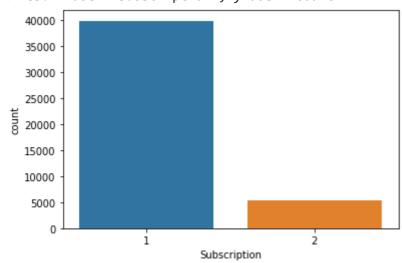
#Subscription column value counts
df['Subscription'].value counts()

39922
 5289

Name: Subscription, dtype: int64

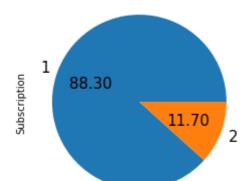
#Subscription column value counts graph
sns.countplot(x='Subscription',data=df)

<Axes: xlabel='Subscription', ylabel='count'>



#Subscription column Piechart
df['Subscription'].value\_counts().plot(kind='pie',fontsize=15,autopct='%.2f')
plt.title('Subscription',fontsize=20,color='red')

Text(0.5, 1.0, 'Subscription') **Subscription** 



#### **EACH CATEGORICAL COLUMN VALUE COUNTS**

#Job column value counts
df['Job'].value\_counts()

```
management
                    9458
    technician
                  7597
    admin.
                    5171
                  4154
    services
                  2264
    retired
    self-employed 1579
    entrepreneur 1487
    unemployed
                   1303
    housemaid
                    1240
    student
                    938
                     288
    unknown
    Name: Job, dtype: int64
#Martial status column value counts
df['Marital Status'].value_counts()
               27214
    married
               12790
    single
    divorced
                5207
    Name: Marital Status, dtype: int64
#Education column value counts
df['Education'].value_counts()
    secondary
                23202
    tertiary
                13301
    primary
                 6851
                 1857
    unknown
    Name: Education, dtype: int64
#Credit column value counts
df['Credit'].value_counts()
    no
           44396
             815
    yes
    Name: Credit, dtype: int64
#Housing Loan column value counts
df['Housing Loan'].value counts()
    yes
           25130
           20081
    no
    Name: Housing Loan, dtype: int64
#Personal Loan column value counts
df['Personal Loan'].value counts()
           37967
    no
           7244
    yes
    Name: Personal Loan, dtype: int64
#Contact column value counts
df['Contact'].value_counts()
```

blue-collar

9732

```
cellular 29285
unknown 13020
telephone 2906
```

Name: Contact, dtype: int64

#Last Contact Month column value counts
df['Last Contact Month'].value\_counts()

13766 may jul 6895 6247 aug 5341 jun 3970 nov apr 2932 feb 2649 1403 jan oct 738 579 sep 477 mar dec 214

Name: Last Contact Month, dtype: int64

#Poutcome column value counts
df['Poutcome'].value\_counts()

unknown 36959 failure 4901 other 1840 success 1511

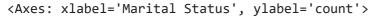
Name: Poutcome, dtype: int64

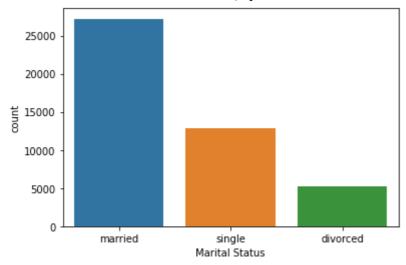
#### **COUNTPLOT EACH CATEGORICAL COLUMN**

#Job column value counts graph
sns.countplot(x='Job',data=df)
plt.xticks(rotation=90)

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]),
[Text(0,  0, 'management'),
  Text(1,  0, 'technician'),
  Text(2,  0, 'entrepreneur'),
  Text(3,  0, 'blue-collar'),
  Text(4,  0, 'unknown'),
  Text(5,  0, 'retired'),
  Text(6,  0, 'admin.'),
  Text(7,  0, 'services'),
  Text(8,  0, 'self-employed'),
  Text(9,  0, 'unemployed')
```

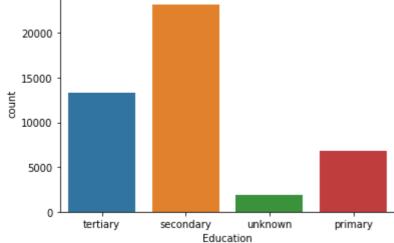
#Marital Status column value counts graph
sns.countplot(x='Marital Status',data=df)





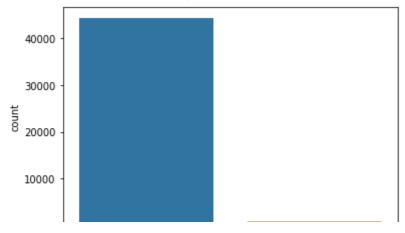
#Education column value counts graph
sns.countplot(x='Education',data=df)





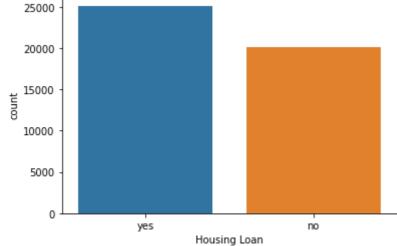
#Credit column value counts graph
sns.countplot(x='Credit',data=df)

<Axes: xlabel='Credit', ylabel='count'>



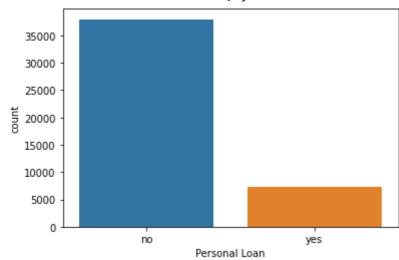
#Housing Loan column value counts graph
sns.countplot(x='Housing Loan',data=df)

<Axes: xlabel='Housing Loan', ylabel='count'>
25000



#Personal Loan column value counts graph
sns.countplot(x='Personal Loan',data=df)

<Axes: xlabel='Personal Loan', ylabel='count'>

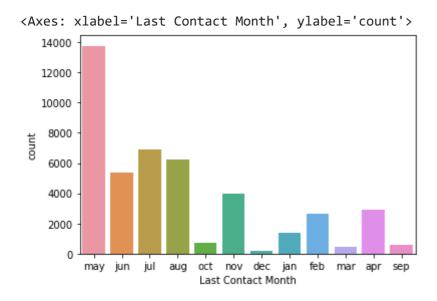


#Contact column value counts graph
sns.countplot(x='Contact',data=df)

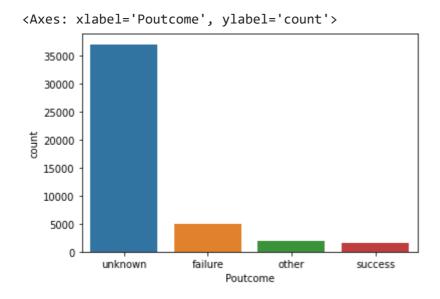
<Axes: xlabel='Contact', ylabel='count'>

30000
25000
10000
10000
unknown cellular telephone
Contact

#Last Contact Month column value counts graph
sns.countplot(x='Last Contact Month',data=df)



#Poutcome column value counts graph
sns.countplot(x='Poutcome',data=df)



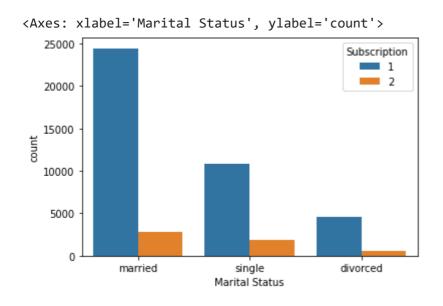
#### Checking the relationship between categorical column and target column

```
#Job column vs target column realtionship
sns.countplot(x='Job',data=df,hue='Subscription')
plt.xticks(rotation=90)
```

```
(array([ 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]),
 [Text(0, 0, 'management'),
  Text(1, 0, 'technician'),
  Text(2, 0, 'entrepreneur'),
  Text(3, 0, 'blue-collar'),
  Text(4, 0, 'unknown'),
  Text(5, 0, 'retired'),
  Text(6, 0, 'admin.'),
  Text(7, 0, 'services'),
  Text(8, 0, 'self-employed'),
  Text(9, 0, 'unemployed'),
  Text(10, 0, 'housemaid'),
  Text(11, 0, 'student')])
                                                     Subscription
                                                         1
   8000
                                                           2
   6000
   4000
   2000
                                               self-employed
                                                        housemaid
              technician
                   entrepreneur
                                 retired
                                          services
                                                   unemployed
                       blue-collar
                            unknown
                                      admin.
                                                             student
          management
```

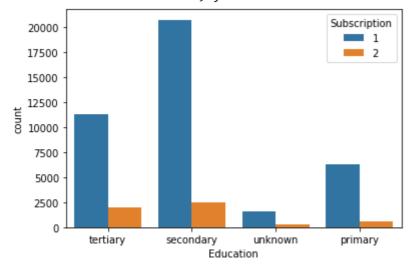
#Marital Status column vs target column realtionship
sns.countplot(x='Marital Status',data=df,hue='Subscription')

Job

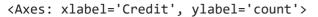


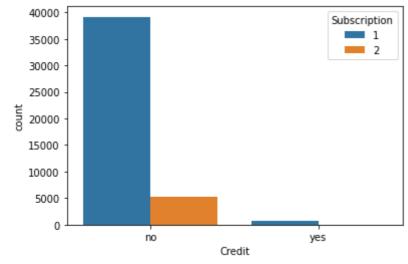
#Education column vs target column realtionship
sns.countplot(x='Education',data=df,hue='Subscription')

<Axes: xlabel='Education', ylabel='count'>



#Credit column vs target column realtionship
sns.countplot(x='Credit',data=df,hue='Subscription')



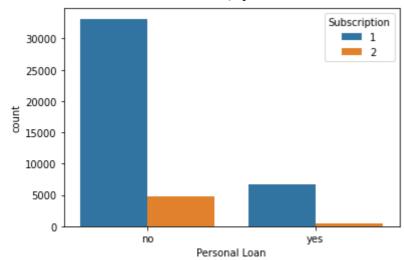


#Housing Loan column vs target column realtionship
sns.countplot(x='Housing Loan',data=df,hue='Subscription')

<Axes: xlabel='Housing Loan', ylabel='count'>

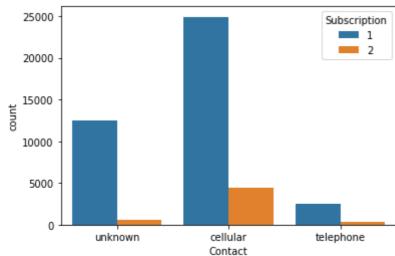
#Personal Loan column vs target column realtionship
sns.countplot(x='Personal Loan',data=df,hue='Subscription')

<Axes: xlabel='Personal Loan', ylabel='count'>



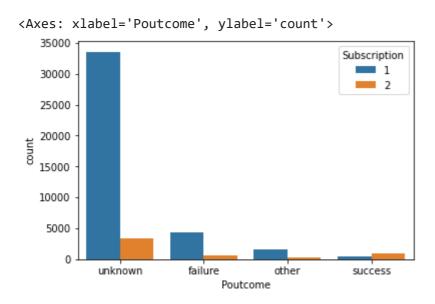
#Contact column vs target column realtionship
sns.countplot(x='Contact',data=df,hue='Subscription')

<Axes: xlabel='Contact', ylabel='count'>



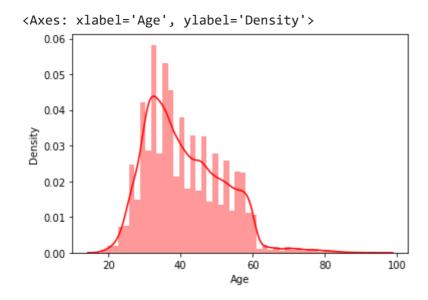
#Last Contact Month vs target column realtionship
sns.countplot(x='Last Contact Month',data=df,hue='Subscription')

#Poutcome column vs target column realtionship
sns.countplot(x='Poutcome',data=df,hue='Subscription')



#### **DISTPLOT-depicts the variation in data distribution**

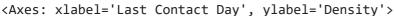
#Age Column distribution Plot
sns.distplot(df['Age'],color='red')

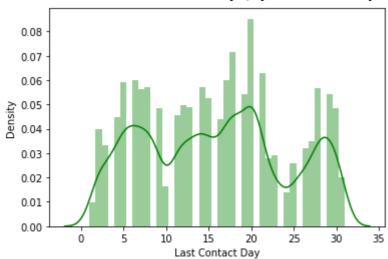


#Balance (euros) Column distribution Plot
sns.distplot(df['Balance (euros)'],color='blue')

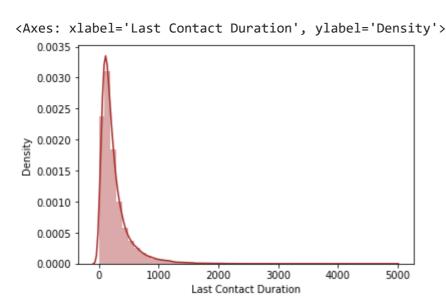
<Axes: xlabel='Balance (euros)', ylabel='Density'>
0.0004
0.0003

#Last Contact Day Column distribution Plot
sns.distplot(df['Last Contact Day'],color='green')





#Last Contact Duration Column distribution Plot
sns.distplot(df['Last Contact Duration'],color='brown')

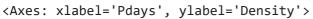


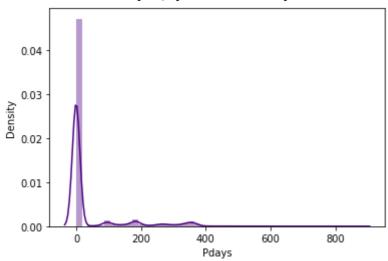
#Campaign Column distribution Plot
sns.distplot(df['Campaign'],color='black')

<Axes: xlabel='Campaign', ylabel='Density'>

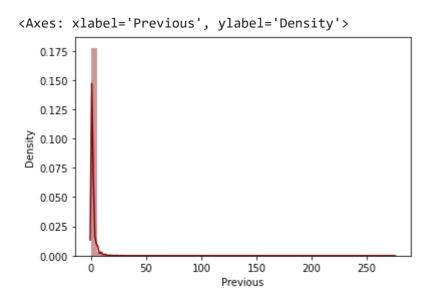
0.5 0.4 
\$\frac{1}{20}\$ 0.3 -

#Pdays Column distribution Plot
sns.distplot(df['Pdays'],color='indigo')





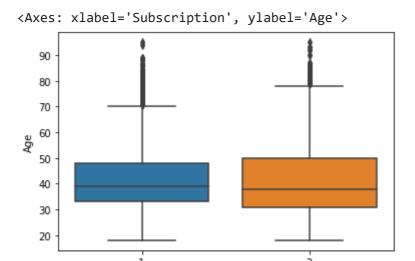
#Previous Column distribution Plot
sns.distplot(df['Previous'],color='maroon')



#Subscription Column distribution Plot
sns.distplot(df['Subscription'],color='grey')

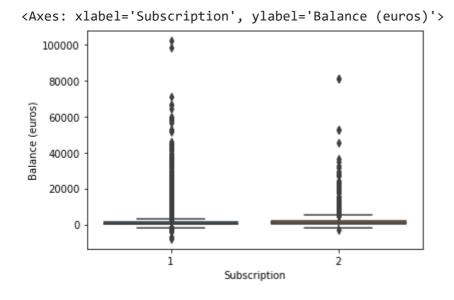


#How Age Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Age',data=df)



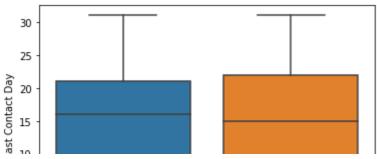
#How Balance (euros) Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Balance (euros)',data=df)

Subscription



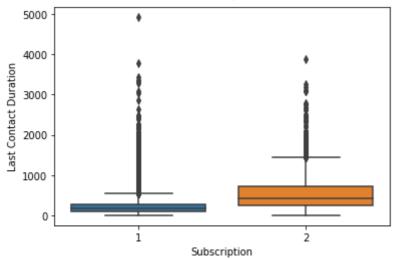
#How Last Contact Day Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Last Contact Day',data=df)

<Axes: xlabel='Subscription', ylabel='Last Contact Day'>



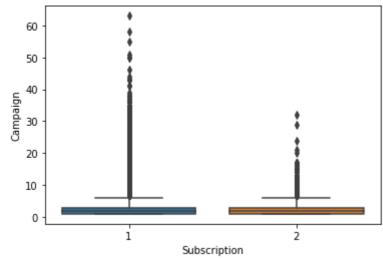
#How Last Contact Duration Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Last Contact Duration',data=df)

<Axes: xlabel='Subscription', ylabel='Last Contact Duration'>



#How Campaign Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Campaign',data=df)

<Axes: xlabel='Subscription', ylabel='Campaign'>

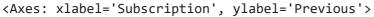


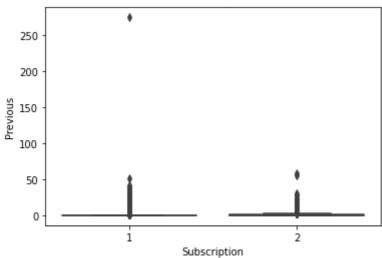
#How Pdays Column Affect Subsription Column
sns.boxplot(x='Subscription',y='Pdays',data=df)

<Axes: xlabel='Subscription', ylabel='Pdays'>

800 - 6

#How Previous Column Affect Subscription Column
sns.boxplot(x='Subscription',y='Previous',data=df)





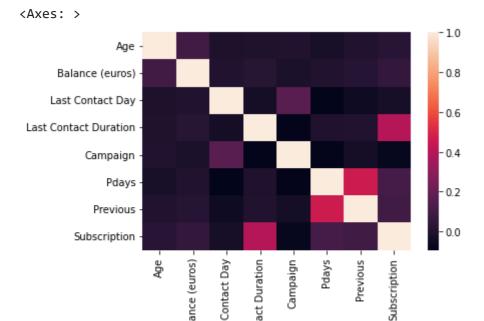
#### **CORRELATION**

df.corr()

	Age	Balance (euros)	Last Contact Day	Last Contact Duration	Campaign	Pdays	Previous	Subsc
Age	1.000000	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288	
Balance (euros)	0.097783	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674	
Last Contact Day	-0.009120	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710	-
Last Contact Duration	-0.004648	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203	
Campaign	0.004760	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855	-
Pdave	_N N23758	Ი	_n ng3n44	_0 001565	_n naaraa	1 000000	N 45482N	

#### **HEATMAP-CORRELATION SHOWING**

sns.heatmap(df.corr())



#### **Encoding string to Numeric using LabelEncoding**

\_

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df['Housing Loan']=le.fit_transform(df['Housing Loan'])
df['Housing Loan']
```

```
0
         1
1
         1
2
         1
3
         1
4
         0
45206
         0
45207
         0
45208
         0
45209
45210
Name: Housing Loan, Length: 45211, dtype: int64
```

df['Personal Loan']=le.fit\_transform(df['Personal Loan'])
df['Personal Loan']

```
0
          0
1
          0
2
          1
3
          0
4
          0
45206
          0
45207
          0
45208
          0
45209
45210
```

Name: Personal Loan, Length: 45211, dtype: int64

Age	int64
Job	object
Marital Status	object
Education	object
Credit	object
Balance (euros)	int64
Housing Loan	int64
Personal Loan	int64
Contact	object
Last Contact Day	int64
Last Contact Month	object
Last Contact Duration	int64
Campaign	int64
Pdays	int64
Previous	int64
Poutcome	object
Subscription	int64
dtype: object	

dtype: object

## **Encoding string to Numeric using GETDUMMIES**

df1=pd.get\_dummies(df[['Job','Marital Status','Education','Credit','Contact', 'Last Contact Month','Poutcome']],drop\_first=True) df1

	Job_blue- collar	Job_entrepreneur	Job_housemaid	Job_management	Job_retired	Job_self- employed	Job
0	0	0	0	1	0	0	
1	0	0	0	0	0	0	
2	0	1	0	0	0	0	
3	1	0	0	0	0	0	
4	0	0	0	0	0	0	
45206	0	0	0	0	0	0	
45207	0	0	0	0	1	0	
45208	0	0	0	0	1	0	
45209	1	0	0	0	0	0	
45210	0	1	0	0	0	0	

45211 rows × 33 columns



## **Concatination-combining**

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

Age		Job	Marital Education C Status		Credit	Balance (euros)	Housing Loan	Personal Loan	Contact	L Cont
0	58	management	married	tertiary	no	2143	1	0	unknown	
1	44	technician	single	secondary	no	29	1	0	unknown	
2	33	entrepreneur	married	secondary	no	2	1	1	unknown	
3	47	blue-collar	married	unknown	no	1506	1	0	unknown	
4	33	unknown	single	unknown	no	1	0	0	unknown	
45206	51	technician	married	tertiary	no	825	0	0	cellular	
45207	71	retired	divorced	primary	no	1729	0	0	cellular	
45208	72	retired	married	secondary	no	5715	0	0	cellular	
45209	57	blue-collar	married	secondary	no	668	0	0	telephone	
45210	37	entrepreneur	married	secondary	no	2971	0	0	cellular	

45211 rows × 50 columns



	Age	Balance (euros)	Housing Loan	Personal Loan	Last Contact Day	Last Contact Duration	Campaign	Pdays	Previous	Subscript
0	58	2143	1	0	5	261	1	-1	0	

#### dfe.dtypes

```
int64
Age
Balance (euros)
                           int64
Housing Loan
                           int64
Personal Loan
                           int64
Last Contact Day
                           int64
Last Contact Duration
                           int64
Campaign
                           int64
Pdays
                           int64
Previous
                           int64
Subscription
                           int64
Job blue-collar
                           uint8
Job_entrepreneur
                           uint8
Job_housemaid
                           uint8
Job management
                           uint8
Job retired
                           uint8
Job_self-employed
                           uint8
Job_services
                           uint8
Job_student
                           uint8
Job_technician
                           uint8
Job unemployed
                           uint8
Job_unknown
                           uint8
Marital Status married
                           uint8
Marital Status_single
                           uint8
Education_secondary
                           uint8
Education tertiary
                           uint8
Education_unknown
                           uint8
Credit_yes
                           uint8
Contact_telephone
                           uint8
Contact_unknown
                           uint8
Last Contact Month aug
                           uint8
Last Contact Month dec
                           uint8
Last Contact Month_feb
                           uint8
Last Contact Month_jan
                           uint8
Last Contact Month_jul
                           uint8
Last Contact Month jun
                           uint8
Last Contact Month mar
                           uint8
Last Contact Month_may
                           uint8
Last Contact Month_nov
                           uint8
Last Contact Month_oct
                           uint8
Last Contact Month sep
                           uint8
Poutcome other
                           uint8
Poutcome_success
                           uint8
Poutcome_unknown
                           uint8
dtype: object
```

```
#Seperate x
x=dfe.drop(['Subscription'],axis=1)
```

	Age	Balance (euros)	Housing Loan	Personal Loan	Last Contact Day	Last Contact Duration	Campaign	Pdays	Previous	Job_blue- collar
0	58	2143	1	0	5	261	1	-1	0	C
1	44	29	1	0	5	151	1	-1	0	C
2	33	2	1	1	5	76	1	-1	0	C
3	47	1506	1	0	5	92	1	-1	0	1
4	33	1	0	0	5	198	1	-1	0	C
45206	51	825	0	0	17	977	3	-1	0	(
45207	71	1729	0	0	17	456	2	-1	0	C
45208	72	5715	0	0	17	1127	5	184	3	C
45209	57	668	0	0	17	508	4	-1	0	1
45210	37	2971	0	0	17	361	2	188	11	C

15211 rowe x 12 columns

```
#Seperate y
y=dfe['Subscription']
y
```

Name: Subscription, Length: 45211, dtype: int64

## Split-Train,Test

from sklearn.model\_selection import train\_test\_split
x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,test\_size=0.30,random\_state=42)
x\_train

	Age	Balance (euros)	Housing Loan	Personal Loan	Last Contact Day		Campaign	Pdays	Previous	Job_blue- collar
10747	36	0	0	0	17	153	4	-1	0	C
26054	56	196	0	0	19	312	3	-1	0	(
9125	46	0	1	0	5	83	2	-1	0	1
41659	41	3426	0	0	1	302	1	119	5	(
4443	38	0	1	0	20	90	1	-1	0	1
11284	44	1059	0	0	18	2093	1	-1	0	(
44700	00	500	0	^	0	040	A	00	A	,

 $x\_test$ 

	Age	Balance (euros)	Housing Loan	Personal Loan	Last Contact Day	Last Contact Duration	Campaign	Pdays	Previous	Job_blue- collar
3776	40	580	1	0	16	192	1	-1	0	1
9928	47	3644	0	0	9	83	2	-1	0	(
33409	25	538	1	0	20	226	1	-1	0	(
31885	42	1773	0	0	9	311	1	336	1	(
15738	56	217	0	1	21	121	2	-1	0	(
9016	46	2800	0	0	5	47	1	-1	0	(
380	38	757	1	0	6	133	1	-1	0	1
7713	41	4539	0	0	30	298	3	-1	0	C
12188	41	1309	0	0	20	28	4	-1	0	C
28550	57	1016	1	0	29	462	2	234	5	(

13564 rows × 42 columns



## y\_train

10747	1
26054	1
9125	1
41659	1
4443	1
11284	2
44732	1
38158	1
860	1

```
y_test
    3776
          1
    9928
    33409
           1
    31885
          1
    15738 1
           . .
    9016
          1
    380
    7713
           1
    12188
           1
    28550
    Name: Subscription, Length: 13564, dtype: int64
Normalization using MinMaxscaler
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
scaler.fit(x_train)
x_train=scaler.fit_transform(x_train)
x_train
                                 , ..., 0. , 0.
    array([[0.23376623, 0.07776175, 0.
          1. ],
          [0.49350649, 0.07998773, 0.
                                       , ..., 0.
                                                     , 0.
                                                      , 0.
          [0.36363636, 0.07776175, 1.
                                       , ..., 0.
           1.
               ],
          [0.20779221, 0.09271899, 1.
                                                      , 0.
                                       , ..., 0.
           1. ],
          [0.19480519, 0.07963567, 0.
                                       , ..., 0.
                                                     , 0.
          1. ],
          [0.25974026, 0.07729611, 1.
                                       , ..., 0.
                                                      , 0.
           1. ]])
x_test=scaler.fit_transform(x_test)
x test
    array([[0.29333333, 0.07806911, 1.
                                   , ..., 0.
                                                     , 0.
           1. ],
          [0.38666667, 0.10588673, 0.
                                       , ..., 0.
                                                      , 0.
           1. ],
          [0.09333333, 0.0776878 , 1. , ..., 0.
                                                      , 0.
           1. ],
          [0.30666667, 0.11401231, 0.
                                       , ..., 0.
                                                      , 0.
           1. ],
          [0.30666667, 0.0846876, 0. , ..., 0.
                                                      , 0.
          1.
                   ],
                   , 0.08202749, 1. , ..., 0.
          [0.52
                                                      , 0.
           0.
                   ]])
```

15795

Name: Subscription, Length: 31647, dtype: int64

## MODEL CREATION KNN

```
from sklearn.neighbors import KNeighborsClassifier
modelkn=KNeighborsClassifier(n_neighbors=3)
modelkn.fit(x_train,y_train)
y_predkn=modelkn.predict(x_test)
y_predkn
array([1, 1, 1, ..., 1, 1])
```

#### PERFOMANCE EVALUATION

from sklearn.metrics import confusion\_matrix,accuracy\_score,classification\_report
resultkn=confusion\_matrix(y\_test,y\_predkn)
resultkn

```
array([[11496, 470], [ 1107, 491]])
```

scorekn=accuracy\_score(y\_test,y\_predkn)
scorekn

0.8837363609554704

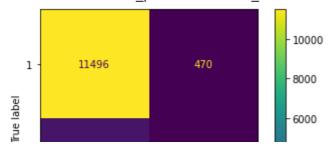
print(classification report(y test,y predkn))

support	f1-score	recall	precision	
11966	0.94	0.96	0.91	1
1598	0.38	0.31	0.51	2
13564	0.88			accuracy
13564	0.66	0.63	0.71	macro avg
13564	0.87	0.88	0.86	weighted avg

#### **Display confusion Metrics**

```
from sklearn.metrics._plot.confusion_matrix import ConfusionMatrixDisplay
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay
cm=['1','2']
cmd=ConfusionMatrixDisplay(resultkn,display_labels=cm)
cmd.plot()
```

<sklearn.metrics.\_plot.confusion\_matrix.ConfusionMatrixDisplay at 0x7fd1b3f02100>



## MODEL CREATION DECISIONTREECLASSIFIER

```
from sklearn.tree import DecisionTreeClassifier
modeldt=DecisionTreeClassifier()
modeldt.fit(x_train,y_train)
y_preddt=modeldt.predict(x_test)
y_preddt
```

### array([1, 1, 1, ..., 1, 1, 1])

#### **Perfomance Evaluation**

from sklearn.metrics import confusion\_matrix,accuracy\_score,classification\_report
resultdt=confusion\_matrix(y\_test,y\_preddt)
resultdt

```
array([[10424, 1542], [ 753, 845]])
```

scoredt=accuracy\_score(y\_test,y\_preddt)
scoredt

0.8308021232674727

print(classification\_report(y\_test,y\_preddt))

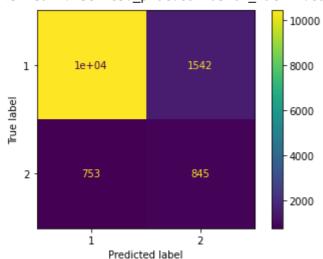
	precision	recall	f1-score	support
1 2	0.93 0.35	0.87 0.53	0.90 0.42	11966 1598
_				
accuracy			0.83	13564
macro avg	0.64	0.70	0.66	13564
weighted avg	0.86	0.83	0.84	13564

#### **Display confusion metrics**

from sklearn.metrics.\_plot.confusion\_matrix import ConfusionMatrixDisplay
from sklearn.metrics import confusion\_matrix,ConfusionMatrixDisplay
cm=['1','2']

cmd=ConfusionMatrixDisplay(resultdt,display\_labels=cm)
cmd.plot()

<sklearn.metrics.\_plot.confusion\_matrix.ConfusionMatrixDisplay at 0x7fd1b3e98e80>



## MODEL CREATION RANDOMFORESTCLASSIFIER

```
from sklearn.ensemble import RandomForestClassifier
modelrf=RandomForestClassifier(n_estimators=4,criterion='entropy')
modelrf.fit(x_train,y_train)
y_predrf=modelrf.predict(x_test)
y_predrf
array([1, 1, 2, ..., 1, 1, 2])
```

#### **Perfomance Evaluation**

from sklearn.metrics import confusion\_matrix,accuracy\_score,classification\_report
resultrf=confusion\_matrix(y\_test,y\_predrf)
resultrf

```
array([[11433, 533], [ 1046, 552]])
```

scorerf=accuracy\_score(y\_test,y\_predrf)
scorerf

0.8835889118254202

print(classification\_report(y\_test,y\_predrf))

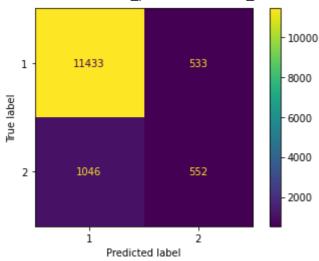
	precision	recall	f1-score	support
1	0.92	0.96	0.94	11966
2	0.51	0.35	0.41	1598
accuracy			0.88	13564
macro avg	0.71	0.65	0.67	13564

weighted avg 0.87 0.88 0.87 13564

#### **Display Confusion Metrics**

from sklearn.metrics.\_plot.confusion\_matrix import ConfusionMatrixDisplay
from sklearn.metrics import confusion\_matrix,ConfusionMatrixDisplay
cm=['1','2']
cmd=ConfusionMatrixDisplay(resultrf,display\_labels=cm)
cmd.plot()

<sklearn.metrics.\_plot.confusion\_matrix.ConfusionMatrixDisplay at 0x7fd1b3dcbd00>



## MODEL CREATION NAIVEBAYES

```
from sklearn.naive_bayes import MultinomialNB
modelnb=MultinomialNB()
modelnb.fit(x_train,y_train)
y_prednb=modelnb.predict(x_test)
y_prednb
```

#### **Perfomance Evaluation**

from sklearn.metrics import confusion\_matrix,accuracy\_score,classification\_report
resultnb=confusion\_matrix(y\_test,y\_prednb)
resultnb

```
array([[11603, 363], [ 1150, 448]])
```

scorenb=accuracy\_score(y\_test,y\_prednb)
scorenb

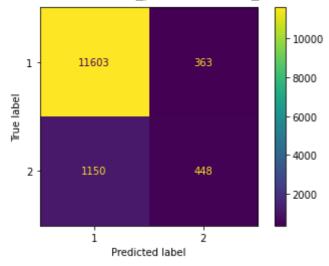
print(classification\_report(y\_test,y\_prednb))

	precision	recall	f1-score	support
1	0.91	0.97	0.94	11966
2	0.55	0.28	0.37	1598
accuracy			0.89	13564
macro avg	0.73	0.63	0.66	13564
weighted avg	0.87	0.89	0.87	13564

#### **Display Confusion matrix**

from sklearn.metrics.\_plot.confusion\_matrix import ConfusionMatrixDisplay
from sklearn.metrics import confusion\_matrix,ConfusionMatrixDisplay
cm=['1','2']
cmd=ConfusionMatrixDisplay(resultnb,display\_labels=cm)
cmd.plot()

<sklearn.metrics.\_plot.confusion\_matrix.ConfusionMatrixDisplay at 0x7fd1b3d76e20>



## MODEL CREATION SVM

```
from sklearn.svm import SVC
svmodel=SVC()
svmodel.fit(x_train,y_train)
y_predsv=svmodel.predict(x_test)
y_predsv
array([1, 1, 1, ..., 1, 1, 1])
```

#### **Perfomance Evaluation**

from sklearn.metrics import confusion\_matrix,accuracy\_score,classification\_report
resultsv=confusion\_matrix(y\_test,y\_predsv)
resultsv

```
array([[11761, 205], [ 1173, 425]])
```

scoresv=accuracy\_score(y\_test,y\_predsv)
scoresv

0.8984075493954585

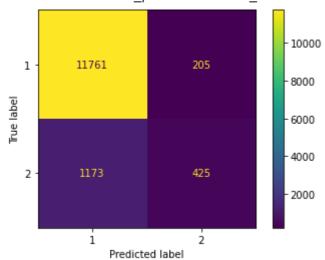
print(classification\_report(y\_test,y\_predsv))

	precision	recall	f1-score	support
1 2	0.91 0.67	0.98 0.27	0.94 0.38	11966 1598
accuracy macro avg weighted avg	0.79 0.88	0.62 0.90	0.90 0.66 0.88	13564 13564 13564

#### **Display Confusion matrix**

from sklearn.metrics.\_plot.confusion\_matrix import ConfusionMatrixDisplay
from sklearn.metrics import confusion\_matrix,ConfusionMatrixDisplay
cm=['1','2']
cmd=ConfusionMatrixDisplay(resultsv,display\_labels=cm)
cmd.plot()

<sklearn.metrics.\_plot.confusion\_matrix.ConfusionMatrixDisplay at 0x7fd1b543ad60>



#### **ACCURACY SCORE EACH ALGORITHMS**

```
print("accuracy score in KNN algorithm is",accuracy_score(y_test,y_predkn))
print("accuracy score in DECISON TREE algorithm is",accuracy_score(y_test,y_preddt))
print("accuracy score in RANDOMFORESTCLASSIFIER algorithm is",accuracy_score(y_test,y_p
print("accuracy score in SVM algorithm is",accuracy_score(y_test,y_predsv))
```

print("accuracy score in NAIVE BAYES algorithm is",accuracy\_score(y\_test,y\_prednb))

```
accuracy score in KNN algorithm is 0.8837363609554704
accuracy score in DECISON TREE algorithm is 0.8326452373930994
accuracy score in RANDOMFORESTCLASSIFIER algorithm is 0.8796815098790917
accuracy score in SVM algorithm is 0.8984075493954585
accuracy score in NAIVE BAYES algorithm is 0.8884547331170746
```

✓ 0s completed at 8:42 PM