Problem Statement

You are working for a new-age insurance company and employ mutiple outreach plans to sell term insurance to your customers. Telephonic marketing campaigns still remain one of the most effective way to reach out to people however they incur a lot of cost. Hence, it is important to identify the customers that are most likely to convert beforehand so that they can be specifically targeted via call. We are given the historical marketing data of the insurance company and are required to build a ML model that will predict if a client will subscribe to the insurance.

Features:

age (numeric) job : type of job marital : marital status educational_qual : education status call_type : contact communication type day: last contact day of the month (numeric) mon: last contact month of year dur: last contact duration, in seconds (numeric) num_calls: number of contacts performed during this campaign and for this client prev_outcome: outcome of the previous marketing campaign (categorical: "unknown","other","failure","success")

Output variable (desired target):

y - has the client subscribed to the insurance

Importing Libraries and Data

In [1]:

```
#Importing Libraries

import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt
%matplotlib inline


# For ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#Importing data
data = pd.read_csv(r"D:\IITM_Final_Project\Customer Conversion Prediction - Customer
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 11 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_qual  45211 non-null  object
 4   call_type       45211 non-null  object
 5   day             45211 non-null  int64 
 6   mon             45211 non-null  object
 7   dur             45211 non-null  int64 
 8   num_calls       45211 non-null  int64 
 9   prev_outcome    45211 non-null  object
 10  y               45211 non-null  object
dtypes: int64(4), object(7)
memory usage: 3.8+ MB
```

In [3]:

```
data.head()
```

Out[3]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_out
0	58	management	married	tertiary	unknown	5	may	261	1	un
1	44	technician	single	secondary	unknown	5	may	151	1	un
2	33	entrepreneur	married	secondary	unknown	5	may	76	1	un
3	47	blue-collar	married	unknown	unknown	5	may	92	1	un
4	33	unknown	single	unknown	unknown	5	may	198	1	un

In [4]:

```
data.columns
```

Out[4]:

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mo
n',
       'dur', 'num_calls', 'prev_outcome', 'y'],
      dtype='object')
```

In [5]:

```
data.shape
```

Out[5]:

```
(45211, 11)
```

In [6]:

```
data.dtypes
#ojbect are categorical datatypes
```

Out[6]:

```
age                int64
job               object
marital           object
education_qual    object
call_type         object
day                int64
mon               object
dur                int64
num_calls          int64
prev_outcome      object
y                 object
dtype: object
```

In [7]:

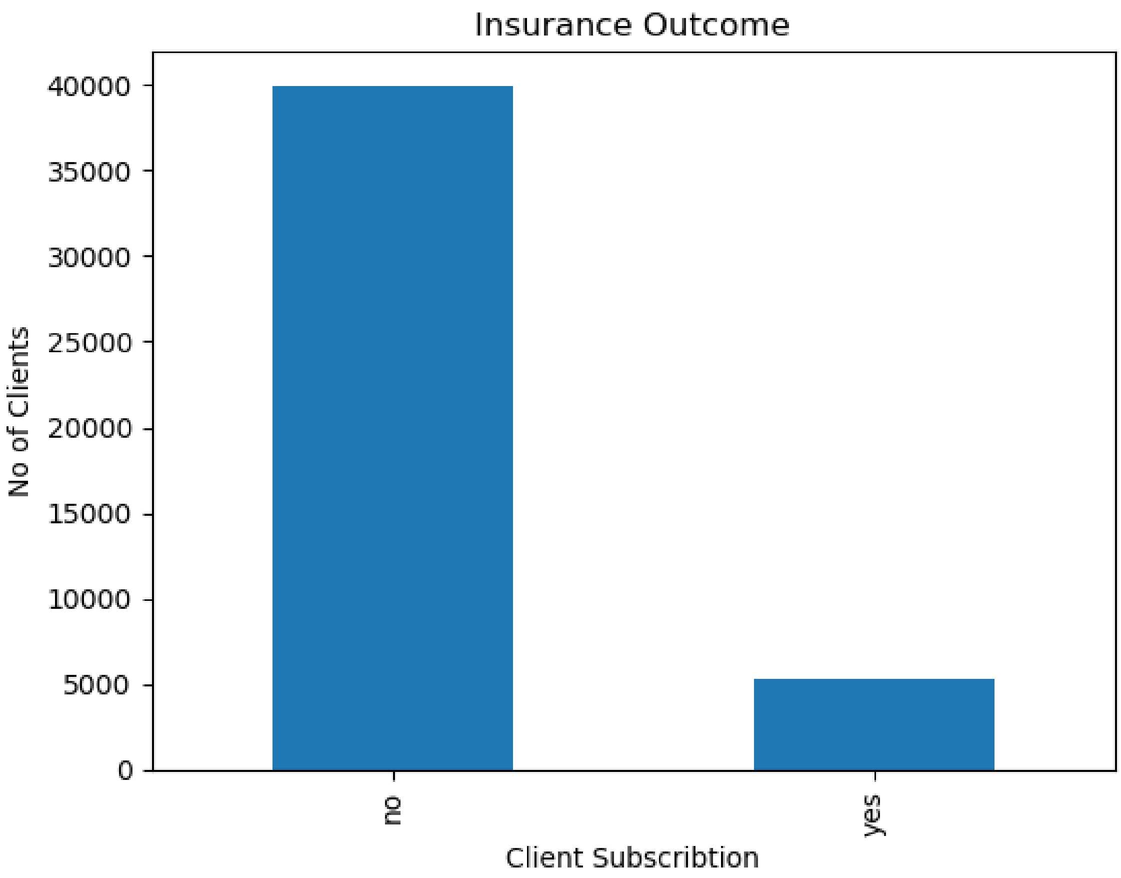
```
#Target variable analysis
print(data['y'].value_counts())

print('\nNot Subscribed - ', round(data['y'].value_counts()['no']/len(data)*100, 2),
print('Subscribed - ', round(data['y'].value_counts()['yes']/len(data)*100, 2), '% c

#Plotting distributiion
data['y'].value_counts().plot(kind='bar')
plt.title('Insurance Outcome')
plt.xlabel('Client Subscribtion')
plt.ylabel('No of Clients')
plt.show()
```

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

Not Subscribed -  88.3 % of the dataset
Subscribed -  11.7 % of the dataset
```



Data Cleaning

In [8]:

```
# checking for null values
data.isnull().sum()
```

Out[8]:

```
age               0
job               0
marital           0
education_qual    0
call_type         0
day               0
mon               0
dur               0
num_calls         0
prev_outcome      0
y                 0
dtype: int64
```

No null values in the data, but we can see there are 'unknown' category which we consider as null values.

In [9]:

```
data[data=='unknown'].count()
```

Out[9]:

```
age                   0
job                 288
marital               0
education_qual     1857
call_type         13020
day                   0
mon                   0
dur                   0
num_calls             0
prev_outcome      36959
y                     0
dtype: int64
```

In [10]:

```
# Dropping the duplicate values
data.drop_duplicates(inplace=True)
```

Job Column

In [11]:

```
data['job'].unique()
```

Out[11]:

```
array(['management', 'technician', 'entrepreneur', 'blue-collar',
       'unknown', 'retired', 'admin.', 'services', 'self-employed',
       'unemployed', 'housemaid', 'student'], dtype=object)
```

In [12]:

```
# Count of unknown values
job_uc = data['job'][data['job']=='unknown'].count()
print("unknown job",job_uc)
#percentage of unknown values
job_ucp = (job_uc/len(data['job']))*100
print(f'{round(job_ucp, 2)}% of job column is unknown')
```

```
unknown job 288
0.64% of job column is unknown
```

In [13]:

```
#Imputing Job Column
# Imputing job column
data['job'].replace('unknown', data['job'].mode()[0], inplace=True)
data['job'].unique()
```

Out[13]:

```
array(['management', 'technician', 'entrepreneur', 'blue-collar',
       'retired', 'admin.', 'services', 'self-employed', 'unemployed',
       'housemaid', 'student'], dtype=object)
```

Martial Column

In [14]:

```
data.marital.unique()
# no unknown values
```

Out[14]:

```
array(['married', 'single', 'divorced'], dtype=object)
```

education_qual column

In [15]:

```
data.education_qual.unique()
```

Out[15]:

```
array(['tertiary', 'secondary', 'unknown', 'primary'], dtype=object)
```

In [16]:

```
eq_uc = data['education_qual'][data['education_qual']=='unknown'].count()
print("unknown education_qual",eq_uc)
eq_ucp = eq_uc/len(data['education_qual'])*100
print(f'{round(eq_ucp, 2)}% of education_qual column is unknown')
# Imputing education_qual Column
data['education_qual'].replace('unknown', data['education_qual'].mode()[0], inplace=
```

```
unknown education_qual 1857
4.11% of education_qual column is unknown
```

Exploratory Data Analysis

In [17]:

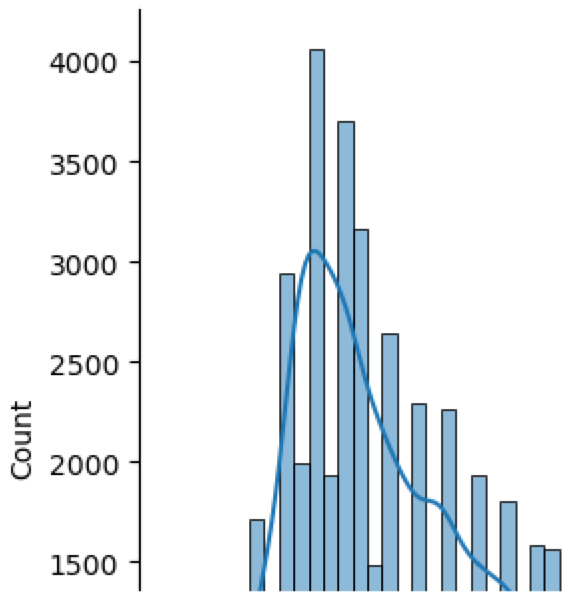
```
num_col=list(data._get_numeric_data())
cat_col=list(data.select_dtypes(include = ['object']))
print("Numerical columns are",num_col)
print("Categorical columns are",cat_col)
```

```
Numerical columns are ['age', 'day', 'dur', 'num_calls']
Categorical columns are ['job', 'marital', 'education_qual', 'call_type',
'mon', 'prev_outcome', 'y']
```

In [18]:

```
for i in num_col:
    plt.figure()
    sns.displot(data=data[i],kde=True,bins=50)
```

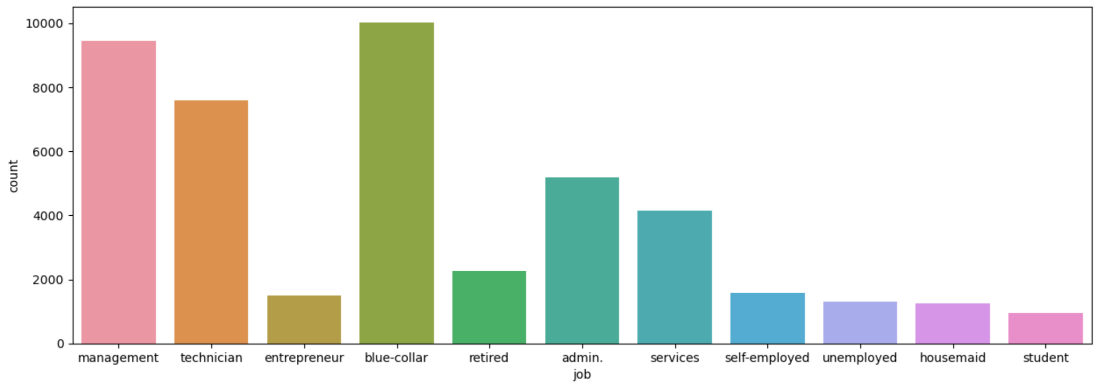
```
<Figure size 640x480 with 0 Axes>
```



In [19]:

```
for i in cat_col:
    plt.figure(figsize=(15,5)),
    sns.countplot(x=data[i],data=data)

```



Encoding

In [20]:

```
#Target column encoding
data['y'] = data['y'].map({'yes':1, 'no':0})
data.head()
```

Out[20]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_out
0	58	management	married	tertiary	unknown	5	may	261	1	unl
1	44	technician	single	secondary	unknown	5	may	151	1	unl
2	33	entrepreneur	married	secondary	unknown	5	may	76	1	unl
3	47	blue-collar	married	secondary	unknown	5	may	92	1	unl
4	33	blue-collar	single	secondary	unknown	5	may	198	1	unl

In [21]:

```
#Job column encoding
job_cat_ord = {'blue-collar':1, 'entrepreneur':2, 'housemaid':3, 'services':4, 'tech
               'admin.':7, 'management':8, 'unemployed':9, 'retired':10, 'student':11
data['job'] = data['job'].map(job_cat_ord)
data.head()
```

Out[21]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	married	tertiary	unknown	5	may	261	1	unknown	0
1	44	5	single	secondary	unknown	5	may	151	1	unknown	0
2	33	2	married	secondary	unknown	5	may	76	1	unknown	0
3	47	1	married	secondary	unknown	5	may	92	1	unknown	0
4	33	1	single	secondary	unknown	5	may	198	1	unknown	0

In [22]:

```
#Marital column encoding
marital_cat_ord = {'married':1, 'divorced':2, 'single':3}
data['marital'] = data['marital'].map(marital_cat_ord)
data.head()
```

Out[22]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	1	tertiary	unknown	5	may	261	1	unknown	0
1	44	5	3	secondary	unknown	5	may	151	1	unknown	0
2	33	2	1	secondary	unknown	5	may	76	1	unknown	0
3	47	1	1	secondary	unknown	5	may	92	1	unknown	0
4	33	1	3	secondary	unknown	5	may	198	1	unknown	0

In [23]:

```
#education_qual column encoding
education_qual_cat_ord = {'primary':1, 'secondary':2, 'tertiary':3}
data['education_qual'] = data['education_qual'].map(education_qual_cat_ord)
data.head()
```

Out[23]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	1	3	unknown	5	may	261	1	unknown	0
1	44	5	3	2	unknown	5	may	151	1	unknown	0
2	33	2	1	2	unknown	5	may	76	1	unknown	0
3	47	1	1	2	unknown	5	may	92	1	unknown	0
4	33	1	3	2	unknown	5	may	198	1	unknown	0

In [24]:

```
#call_type encoding
call_type_cat_ord = {'unknown':1, 'telephone':2, 'cellular':3}
data['call_type'] = data['call_type'].map(call_type_cat_ord)
data.head()
```

Out[24]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	1	3	1	5	may	261	1	unknown	0
1	44	5	3	2	1	5	may	151	1	unknown	0
2	33	2	1	2	1	5	may	76	1	unknown	0
3	47	1	1	2	1	5	may	92	1	unknown	0
4	33	1	3	2	1	5	may	198	1	unknown	0

In [25]:

```
#month column encoding
mon_cat_ord = {'may':1, 'jul':2, 'jan':3, 'nov':4, 'jun':5, 'aug':6, 'feb':7, 'apr':
data['mon'] = data['mon'].map(mon_cat_ord)
data.head()
```

Out[25]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	1	3	1	5	1	261	1	unknown	0
1	44	5	3	2	1	5	1	151	1	unknown	0
2	33	2	1	2	1	5	1	76	1	unknown	0
3	47	1	1	2	1	5	1	92	1	unknown	0
4	33	1	3	2	1	5	1	198	1	unknown	0

In [26]:

```
#prev_outcome encoding
prev_outcome_cat_ord = {'unknown':1, 'failure':2, 'other':3, 'success':4}
data['prev_outcome'] = data['prev_outcome'].map(prev_outcome_cat_ord)
data.head()
```

Out[26]:

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	8	1	3	1	5	1	261	1	1	0
1	44	5	3	2	1	5	1	151	1	1	0
2	33	2	1	2	1	5	1	76	1	1	0
3	47	1	1	2	1	5	1	92	1	1	0
4	33	1	3	2	1	5	1	198	1	1	0

Data Splitting

In [27]:

```
#feature selection
X = data.drop('y', axis=1).values
y = data['y']

```

In [28]:

```
#data splitting
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size = 0.
```

In [29]:

```
#Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Linear Regression Model

In [30]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import RocCurveDisplay
from sklearn.metrics import classification_report
lr = LogisticRegression()
lr.fit(X_train, y_train)
```

Out[30]:

```
▾ LogisticRegression
LogisticRegression()
```

In [31]:

```
print("Confusion Matrix of LogisticRegression Model\n",confusion_matrix(y_test, lr.p
```

```
Confusion Matrix of LogisticRegression Model
 [[9767  213]
 [ 942  380]]
```

In [32]:

```
print("ROC AUC Score of LogisticRegression Model ",roc_auc_score(y_test, lr.predict_
```

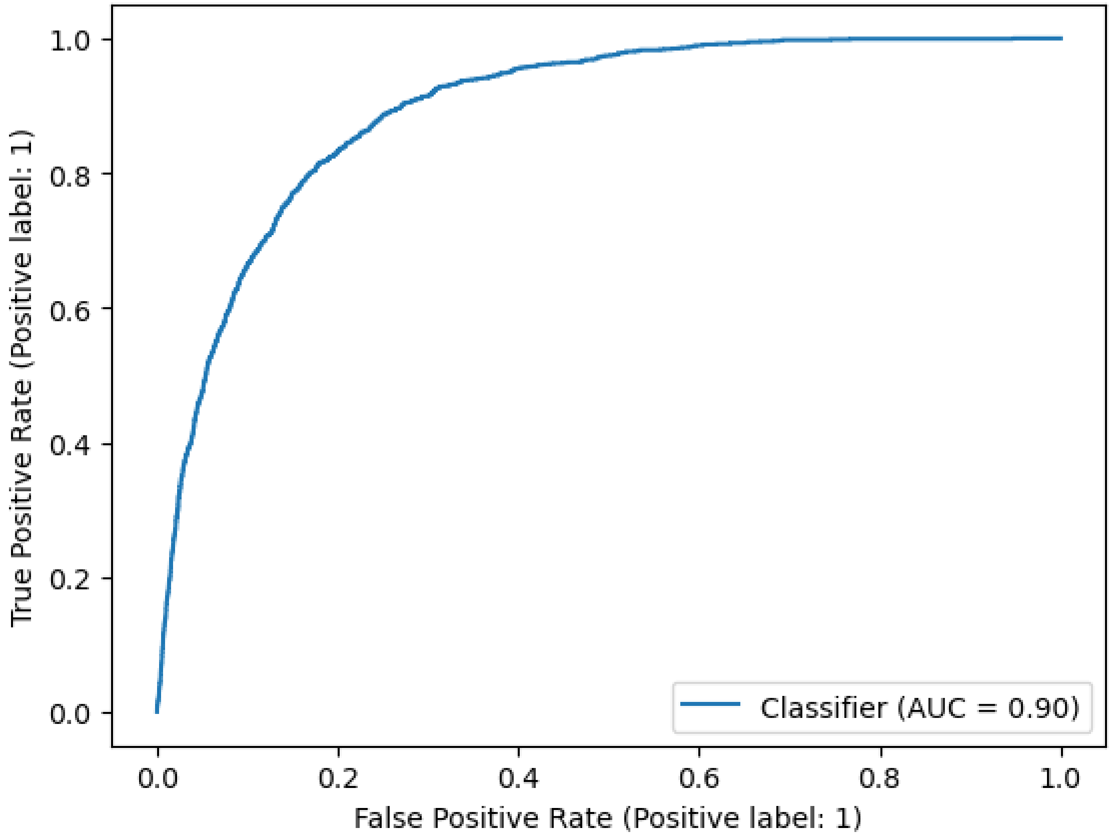
```
ROC AUC Score of LogisticRegression Model  0.8950860874547886
```

In [33]:

```
RocCurveDisplay.from_predictions(y_test, lr.predict_proba(X_test)[:, 1])
```

Out[33]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1e190640790>
```



In [34]:

```
print("Classification of LogisticRegression Model \n\n",classification_report(lr.pre
```

```
Classification of LogisticRegression Model

              precision    recall  f1-score   support

           0       0.98      0.91      0.94     10709
           1       0.29      0.64      0.40       593

    accuracy                           0.90     11302
   macro avg       0.63      0.78      0.67     11302
weighted avg       0.94      0.90      0.92     11302
```

K - Nearest Neighbors

In [35]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

knn = KNeighborsClassifier()
k_range = range(1, 21)
train_scores = []
k_scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    train_score = roc_auc_score(y_train, knn.predict_proba(X_train)[:, 1])
    val_score = np.mean(cross_val_score(knn, X_train, y_train, cv=5, scoring='roc_au
    k_score = val_score
    print(f'K = {k}----Train Score = {train_score}----CV Score = {k_score}')
```

```
K = 1----Train Score = 1.0----CV Score = 0.6805474698080379
K = 2----Train Score = 0.9816713012632141----CV Score = 0.7545456587133581
K = 3----Train Score = 0.971532614675024----CV Score = 0.7900891782259667
K = 4----Train Score = 0.964362975271538----CV Score = 0.815826845106219
K = 5----Train Score = 0.9586269041883082----CV Score = 0.8325778494299222
K = 6----Train Score = 0.9544433047791259----CV Score = 0.8420307730347399
K = 7----Train Score = 0.9510942013662421----CV Score = 0.85091097292099
K = 8----Train Score = 0.9478977764108679----CV Score = 0.8572594231479057
K = 9----Train Score = 0.945291476871523----CV Score = 0.8620455527407822
K = 10----Train Score = 0.9430503416952553----CV Score = 0.866550361264429
5
K = 11----Train Score = 0.941185843975761----CV Score = 0.8698982224445725
K = 12----Train Score = 0.9396773279340771----CV Score = 0.872884588214910
2
K = 13----Train Score = 0.9379849434612679----CV Score = 0.874988773227901
9
K = 14----Train Score = 0.93666638816872----CV Score = 0.8782671667239603
K = 15----Train Score = 0.9355377388912832----CV Score = 0.880913435495020
4
K = 16----Train Score = 0.9345501855096098----CV Score = 0.882922813229577
4
K = 17----Train Score = 0.9335165797613852----CV Score = 0.884763881156378
2
K = 18----Train Score = 0.9325565407530351----CV Score = 0.885879488356666
9
K = 19----Train Score = 0.9319017534019638----CV Score = 0.886471757992637
1
K = 20----Train Score = 0.9310248385363105----CV Score = 0.887503965774054
```

In [36]:

```
knn = KNeighborsClassifier(n_neighbors=11)
knn.fit(X_train, y_train)
```

Out[36]:

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=11)
```

In [37]:

```
1 print("Confusion Matrix of KNeighborsClassifier\n",confusion_matrix(y_test, knn.prec
```

```
Confusion Matrix of KNeighborsClassifier
 [[9708  272]
 [ 856  466]]
```

In [38]:

```
1 print("ROC AUC Score of KNeighborsClassifier",roc_auc_score(y_test, knn.predict_prob
```

```
ROC AUC Score of KNeighborsClassifier 0.8744125922040753
```

In [39]:

```
1 print("Classification of KNeighborsClassifier\n\n",classification_report(y_test, knr
```

```
Classification of KNeighborsClassifier

               precision    recall  f1-score   support

           0       0.92      0.97      0.95      9980
           1       0.63      0.35      0.45      1322

    accuracy                           0.90     11302
   macro avg       0.78      0.66      0.70     11302
weighted avg       0.89      0.90      0.89     11302
```

DecisionTree

In [40]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
for depth in [5,6,7,8,9,10,11,12,13,14,15,20,30,40]:
    dt = DecisionTreeClassifier(max_depth=depth)
    dt.fit(X_train, y_train)
    train_score = roc_auc_score(y_train, dt.predict(X_train))
    dt = DecisionTreeClassifier(max_depth=depth)
    val_score = np.mean(cross_val_score(dt, X_train, y_train, cv=10, scoring='roc_au
    print("Depth  : ", depth, " Training Accuracy : ", train_score, " Cross val scor
```

```
Depth  :  5  Training Accuracy :  0.6784115498830073  Cross val score :
0.8605213774098273
Depth  :  6  Training Accuracy :  0.713595204261992  Cross val score :  0.
8770401773186407
Depth  :  7  Training Accuracy :  0.7206457087446582  Cross val score :
0.879032460888698
Depth  :  8  Training Accuracy :  0.7340240306957843  Cross val score :
0.8749398741296824
Depth  :  9  Training Accuracy :  0.7624361893895616  Cross val score :
0.8617467247876182
Depth  :  10  Training Accuracy :  0.7707150853844053  Cross val score :
0.8472624865897048
Depth  :  11  Training Accuracy :  0.7925365306671541  Cross val score :
0.8207173280681864
Depth  :  12  Training Accuracy :  0.8140482108407187  Cross val score :
0.7960270178218488
Depth  :  13  Training Accuracy :  0.831992735666523  Cross val score :
0.7692698980034427
Depth  :  14  Training Accuracy :  0.852242472370601  Cross val score :
0.7535395297627792
Depth  :  15  Training Accuracy :  0.8816992972959573  Cross val score :
0.7471155627879238
Depth  :  20  Training Accuracy :  0.9660589385075187  Cross val score :
0.7092734335594552
Depth  :  30  Training Accuracy :  0.9996218805142425  Cross val score :
0.6975639961415118
Depth  :  40  Training Accuracy :  1.0  Cross val score :  0.6999121537061
563
```

In [41]:

```
dt = DecisionTreeClassifier(max_depth=11)
dt.fit(X_train, y_train)
```

Out[41]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=11)
```

In [42]:

```
print("Confusion Matrix of DecisionTreeClassifier\n",confusion_matrix(y_test, dt.pre
```

```
Confusion Matrix of DecisionTreeClassifier
 [[9519  461]
 [ 690  632]]
```

In [43]:

```
print("ROC AUC Score of DecisionTreeClassifier",roc_auc_score(y_test, dt.predict_prc
```

```
ROC AUC Score of DecisionTreeClassifier 0.837099046807685
```

In [44]:

```
print("Classification of DecisionTreeClassifier\n\n",classification_report(y_test, c
```

```
Classification of DecisionTreeClassifier

              precision    recall  f1-score   support

           0       0.93      0.95      0.94      9980
           1       0.58      0.48      0.52      1322

    accuracy                           0.90     11302
   macro avg       0.76      0.72      0.73     11302
weighted avg       0.89      0.90      0.89     11302
```

In [ ]:

```

```