# Given a bank customer, build a neural network-based classifier that can determine whether they will leave or not in the next 6 months.

**Dataset Description: The case study is from an open-source dataset from Kaggle. The dataset contains 10,000 sample points with 14 distinct features such as CustomerId, CreditScore, Geography, Gender, Age, Tenure, Balance, etc. Link to the Kaggle project: [https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling](https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling) Perform following steps:**

1. **Read the dataset.**
2. **Distinguish the feature and target set and divide the data set into training and test sets.**
3. **Normalize the train and test data.**
4. **Initialize and build the model. Identify the points of improvement and implement the same.**
5. **Print the accuracy score and confusion matrix.**

In [46]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt #Importing the libraries
```

In [47]:

```
df = pd.read_csv("Churn_Modelling.csv")
```

# Preprocessing.

In [48]:

```
df.head()
```

Out[48]:

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCar |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 |
| **1** | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 |
| **2** | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 |
| **3** | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 |

In [49]:

```
df.shape
```

Out[49]:

```
(10000, 14)
```

In [50]:

```
df.describe()
```

Out[50]:

| | RowNumber | CustomerId | CreditScore | Age | Tenure | Balance | NumOfProducts | HasCrCard | Is |
|---|---|---|---|---|---|---|---|---|---|

| | RowNumber | CustomerId | CreditScore | Age | Tenure | Balance | NumOfProducts | HasCrCard | Is |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 10000.00000 | 1.000000e+04 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.00000 | |
| **mean** | 5000.50000 | 1.569094e+07 | 650.528800 | 38.921800 | 5.012800 | 76485.889288 | 1.530200 | 0.70550 | |
| **std** | 2886.89568 | 7.193619e+04 | 96.653299 | 10.487806 | 2.892174 | 62397.405202 | 0.581654 | 0.45584 | |
| **min** | 1.00000 | 1.556570e+07 | 350.000000 | 18.000000 | 0.000000 | 0.000000 | 1.000000 | 0.00000 | |
| **25%** | 2500.75000 | 1.562853e+07 | 584.000000 | 32.000000 | 3.000000 | 0.000000 | 1.000000 | 0.00000 | |
| **50%** | 5000.50000 | 1.569074e+07 | 652.000000 | 37.000000 | 5.000000 | 97198.540000 | 1.000000 | 1.00000 | |
| **75%** | 7500.25000 | 1.575323e+07 | 718.000000 | 44.000000 | 7.000000 | 127644.240000 | 2.000000 | 1.00000 | |
| **max** | 10000.00000 | 1.581569e+07 | 850.000000 | 92.000000 | 10.000000 | 250898.090000 | 4.000000 | 1.00000 | |

In [51]:

```
df.isnull()
```

Out[51]:

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | False | False | False | False | False | False | False | False | False | False | Fa |
| **1** | False | False | False | False | False | False | False | False | False | False | Fa |
| **2** | False | False | False | False | False | False | False | False | False | False | Fa |
| **3** | False | False | False | False | False | False | False | False | False | False | Fa |
| **4** | False | False | False | False | False | False | False | False | False | False | Fa |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **9995** | False | False | False | False | False | False | False | False | False | False | Fa |
| **9996** | False | False | False | False | False | False | False | False | False | False | Fa |
| **9997** | False | False | False | False | False | False | False | False | False | False | Fa |
| **9998** | False | False | False | False | False | False | False | False | False | False | Fa |
| **9999** | False | False | False | False | False | False | False | False | False | False | Fa |

10000 rows × 14 columns

In [52]:

```
df.isnull().sum()
```

Out[52]:

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [53]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
```

```
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [54]:

```
df.dtypes
```

Out[54]:

```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

In [55]:

```
df.columns
```

Out[55]:

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [56]:

```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the unnecessary columns
```

In [57]:

```
df.head()
```

Out[57]:

| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 |
| **1** | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 |
| **2** | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 |
| **3** | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 |
| **4** | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 |
| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary |

# Visualization

In [101]:

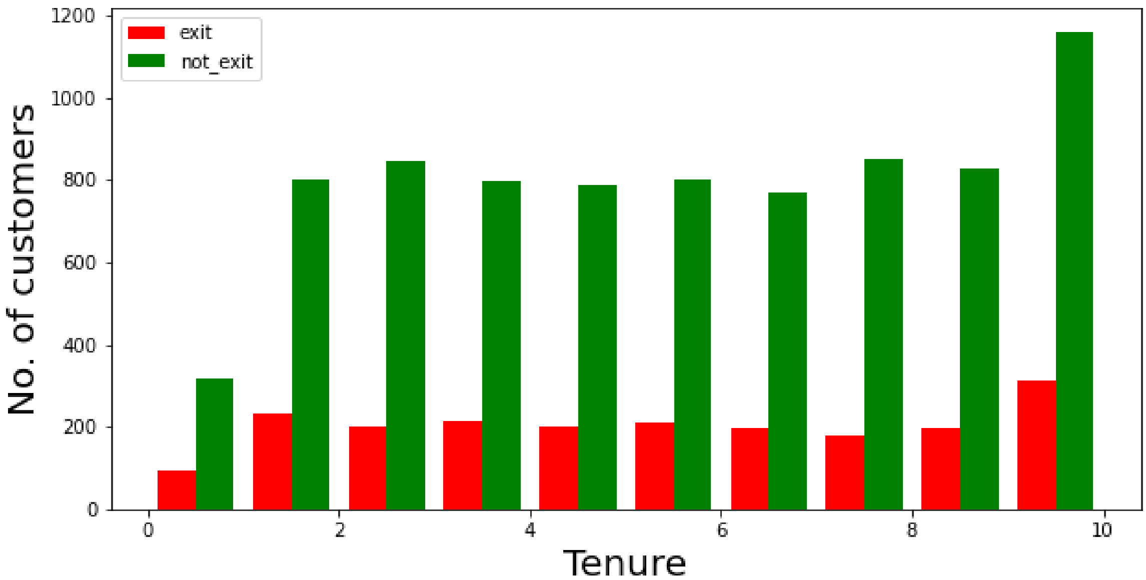
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['red', 'green'], label = ['exit', 'not_exit'])
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel("No. of customers", fontsize=20)
    plt.legend()
```

In [102]:

```
df_churn_exited = df[df['Exited']==1]['Tenure']
df_churn_not_exited = df[df['Exited']==0]['Tenure']
```

In [103]:

```
visualization(df_churn_exited, df_churn_not_exited, "Tenure")
```

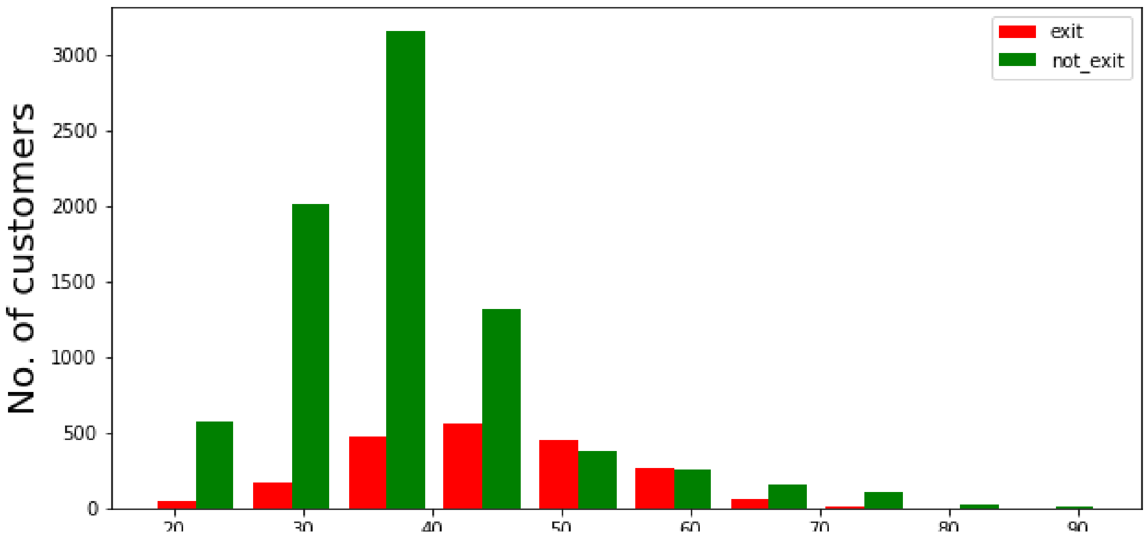



In [105]:

```
df_churn_exited2 = df[df['Exited']==1]['Age']
df_churn_not_exited2 = df[df['Exited']==0]['Age']
```

In [106]:

```
visualization(df_churn_exited2, df_churn_not_exited2, "Age")
```




# Converting the Categorical Variables

In [59]:

```
X = df[['CreditScore','Gender','Age','Tenure','Balance','NumOfProducts','HasCrCard','IsAc
tiveMember','EstimatedSalary']]
states = pd.get_dummies(df['Geography'],drop_first = True)
gender = pd.get_dummies(df['Gender'],drop_first = True)
```

In [61]:

```
df = pd.concat([df,gender,states], axis = 1)
```

# Splitting the training and testing Dataset

In [62]:

```
df.head()
```

Out[62]:

| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 |
| **1** | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 |
| **2** | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 |
| **3** | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 |
| **4** | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 |

In [63]:

```
X = df[['CreditScore','Age','Tenure','Balance','NumOfProducts','HasCrCard','IsActiveMembe
r','EstimatedSalary','Male','Germany','Spain']]
```

In [64]:

```
y = df['Exited']
```

In [65]:

```
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)
```

# Normalizing the values with mean as 0 and Standard Deviation as 1

In [66]:

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

In [67]:

```
X_train  = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [68]:

```
X_train
```

Out[68]:

```
array([[ 4.56838557e-01, -9.45594735e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-2.07591864e-02, -2.77416637e-01,  3.47956411e-01, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.66115021e-01,  1.82257167e+00, -1.38390855e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-3.63383654e-01, -4.68324665e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [ 4.67221117e-01, -1.42286480e+00,  1.38707539e+00, ...,
         9.13181783e-01, -5.81969145e-01,  1.74334114e+00],
       [-8.82511636e-01,  2.95307447e-01, -6.91162564e-01, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

In [69]:

```
X_test
```

Out[69]:

```
array([[ 3.63395520e-01,  1.99853433e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-4.15243057e-02,  4.86215475e-01,  1.58341939e-03, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.87923736e+00, -3.72870651e-01, -1.38390855e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-6.02182526e-01, -5.63778679e-01, -1.73028154e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       [ 1.51585964e+00, -6.59232693e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-5.19122049e-01,  1.04399419e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

# Building the Classifier Model using Keras

In [70]:

```
import keras #Keras is the wrapper on the top of tenserflow
#Can use Tenserflow as well but won't be able to understand the errors initially.
```

In [71]:

```
from keras.models import Sequential #To create sequential neural network
from keras.layers import Dense #To create hidden layers
```

In [72]:

```
classifier = Sequential()
```

In [74]:

```
#To add the layers
#Dense helps to contruct the neurons
#Input Dimension means we have 11 features
# Units is to create the hidden layers
#Uniform helps to distribute the weight uniformly
classifier.add(Dense(activation = "relu",input_dim = 11,units = 6,kernel_initializer = "
uniform"))
```

In [75]:

```
classifier.add(Dense(activation = "relu",units = 6,kernel_initializer = "uniform"))    #A
dding second hidden layers
```

In [76]:

```
classifier.add(Dense(activation = "sigmoid",units = 1,kernel_initializer = "uniform"))  #
Final neuron will be having siigmoid function
```

In [77]:

```
classifier.compile(optimizer="adam",loss = 'binary_crossentropy',metrics = ['accuracy'])
#To compile the Artificial Neural Network. Ussed Binary crossentropy as we just have only
two output
```

In [79]:

```
classifier.summary() #3 layers created. 6 neurons in 1st,6neurons in 2nd layer and 1 neur
on in last
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_3 (Dense)              (None, 6)                 72        
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 42        
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 7         
=================================================================
Total params: 121
Trainable params: 121
Non-trainable params: 0
_________________________________________________________________
```

In [89]:

```
classifier.fit(X_train,y_train,batch_size=10,epochs=50) #Fitting the ANN to training data
set
```

```
Epoch 1/50
700/700 [==============================] - 0s 674us/step - loss: 0.4293 - accuracy: 0.794
7
Epoch 2/50
700/700 [==============================] - 0s 647us/step - loss: 0.4239 - accuracy: 0.794
7
Epoch 3/50
700/700 [==============================] - 0s 657us/step - loss: 0.4203 - accuracy: 0.806
7
Epoch 4/50
700/700 [==============================] - 0s 664us/step - loss: 0.4167 - accuracy: 0.826
0
Epoch 5/50
700/700 [==============================] - 0s 674us/step - loss: 0.4153 - accuracy: 0.828
7
Epoch 6/50
700/700 [==============================] - 0s 653us/step - loss: 0.4137 - accuracy: 0.831
0
Epoch 7/50
700/700 [==============================] - 0s 658us/step - loss: 0.4125 - accuracy: 0.831
7
Epoch 8/50
700/700 [==============================] - 1s 842us/step - loss: 0.4116 - accuracy: 0.830
6
Epoch 9/50
700/700 [==============================] - 0s 671us/step - loss: 0.4103 - accuracy: 0.833
1
Epoch 10/50
700/700 [==============================] - 0s 682us/step - loss: 0.4100 - accuracy: 0.832
6
Epoch 11/50
700/700 [==============================] - 0s 690us/step - loss: 0.4093 - accuracy: 0.833
7
Epoch 12/50
700/700 [==============================] - 0s 688us/step - loss: 0.4087 - accuracy: 0.833
9
```

```
Epoch 13/50
700/700 [==============================] - 0s 675us/step - loss: 0.4081 - accuracy: 0.834
1
Epoch 14/50
700/700 [==============================] - 1s 722us/step - loss: 0.4071 - accuracy: 0.833
1
Epoch 15/50
700/700 [==============================] - 1s 811us/step - loss: 0.4065 - accuracy: 0.834
1
Epoch 16/50
700/700 [==============================] - 0s 711us/step - loss: 0.4056 - accuracy: 0.835
6
Epoch 17/50
700/700 [==============================] - 0s 702us/step - loss: 0.4046 - accuracy: 0.836
6
Epoch 18/50
700/700 [==============================] - 0s 688us/step - loss: 0.4035 - accuracy: 0.834
3
Epoch 19/50
700/700 [==============================] - 1s 715us/step - loss: 0.4024 - accuracy: 0.836
3
Epoch 20/50
700/700 [==============================] - 0s 714us/step - loss: 0.4020 - accuracy: 0.833
7
Epoch 21/50
700/700 [==============================] - 0s 705us/step - loss: 0.4010 - accuracy: 0.837
4
Epoch 22/50
700/700 [==============================] - 1s 720us/step - loss: 0.4003 - accuracy: 0.837
0
Epoch 23/50
700/700 [==============================] - 0s 692us/step - loss: 0.3993 - accuracy: 0.837
4
Epoch 24/50
700/700 [==============================] - 0s 709us/step - loss: 0.3990 - accuracy: 0.835
6
Epoch 25/50
700/700 [==============================] - 1s 871us/step - loss: 0.3984 - accuracy: 0.836
6
Epoch 26/50
700/700 [==============================] - 1s 719us/step - loss: 0.3984 - accuracy: 0.836
7
Epoch 27/50
700/700 [==============================] - 1s 719us/step - loss: 0.3980 - accuracy: 0.836
6
Epoch 28/50
700/700 [==============================] - 0s 695us/step - loss: 0.3981 - accuracy: 0.836
6
Epoch 29/50
700/700 [==============================] - 0s 667us/step - loss: 0.3976 - accuracy: 0.837
4
Epoch 30/50
700/700 [==============================] - 0s 669us/step - loss: 0.3972 - accuracy: 0.837
3
Epoch 31/50
700/700 [==============================] - 0s 670us/step - loss: 0.3970 - accuracy: 0.837
0
Epoch 32/50
700/700 [==============================] - 1s 720us/step - loss: 0.3972 - accuracy: 0.837
6
Epoch 33/50
700/700 [==============================] - 0s 675us/step - loss: 0.3965 - accuracy: 0.836
7
Epoch 34/50
700/700 [==============================] - 0s 680us/step - loss: 0.3961 - accuracy: 0.836
4
Epoch 35/50
700/700 [==============================] - 0s 685us/step - loss: 0.3962 - accuracy: 0.837
9
Epoch 36/50
700/700 [==============================] - 1s 771us/step - loss: 0.3960 - accuracy: 0.837
0
```

```
Epoch 37/50
700/700 [==============================] - 1s 1ms/step - loss: 0.3963 - accuracy: 0.8366
Epoch 38/50
700/700 [==============================] - 1s 764us/step - loss: 0.3962 - accuracy: 0.837
3
Epoch 39/50
700/700 [==============================] - 1s 823us/step - loss: 0.3950 - accuracy: 0.838
4
Epoch 40/50
700/700 [==============================] - 1s 759us/step - loss: 0.3956 - accuracy: 0.836
1
Epoch 41/50
700/700 [==============================] - 1s 773us/step - loss: 0.3949 - accuracy: 0.836
6
Epoch 42/50
700/700 [==============================] - 0s 695us/step - loss: 0.3953 - accuracy: 0.836
9
Epoch 43/50
700/700 [==============================] - 0s 701us/step - loss: 0.3952 - accuracy: 0.836
9
Epoch 44/50
700/700 [==============================] - 0s 707us/step - loss: 0.3952 - accuracy: 0.836
6
Epoch 45/50
700/700 [==============================] - 0s 680us/step - loss: 0.3955 - accuracy: 0.837
6
Epoch 46/50
700/700 [==============================] - 0s 665us/step - loss: 0.3947 - accuracy: 0.837
3
Epoch 47/50
700/700 [==============================] - 0s 708us/step - loss: 0.3947 - accuracy: 0.837
1
Epoch 48/50
700/700 [==============================] - 0s 681us/step - loss: 0.3944 - accuracy: 0.837
1
Epoch 49/50
700/700 [==============================] - 0s 678us/step - loss: 0.3947 - accuracy: 0.838
3
Epoch 50/50
700/700 [==============================] - 1s 869us/step - loss: 0.3944 - accuracy: 0.837
0
```

Out[89]:

```
<tensorflow.python.keras.callbacks.History at 0x1fb1eb93df0>
```

In [90]:

```
y_pred =classifier.predict(X_test)
y_pred = (y_pred > 0.5) #Predicting the result
```

In [97]:

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

In [92]:

```
cm = confusion_matrix(y_test,y_pred)
```

In [93]:

```
cm
```

Out[93]:

```
array([[2328,   72],
       [ 425,  175]], dtype=int64)
```

In [94]:

```
accuracy = accuracy_score(y_test,y_pred)
```

In [95]:

```
accuracy
```

Out[95]:

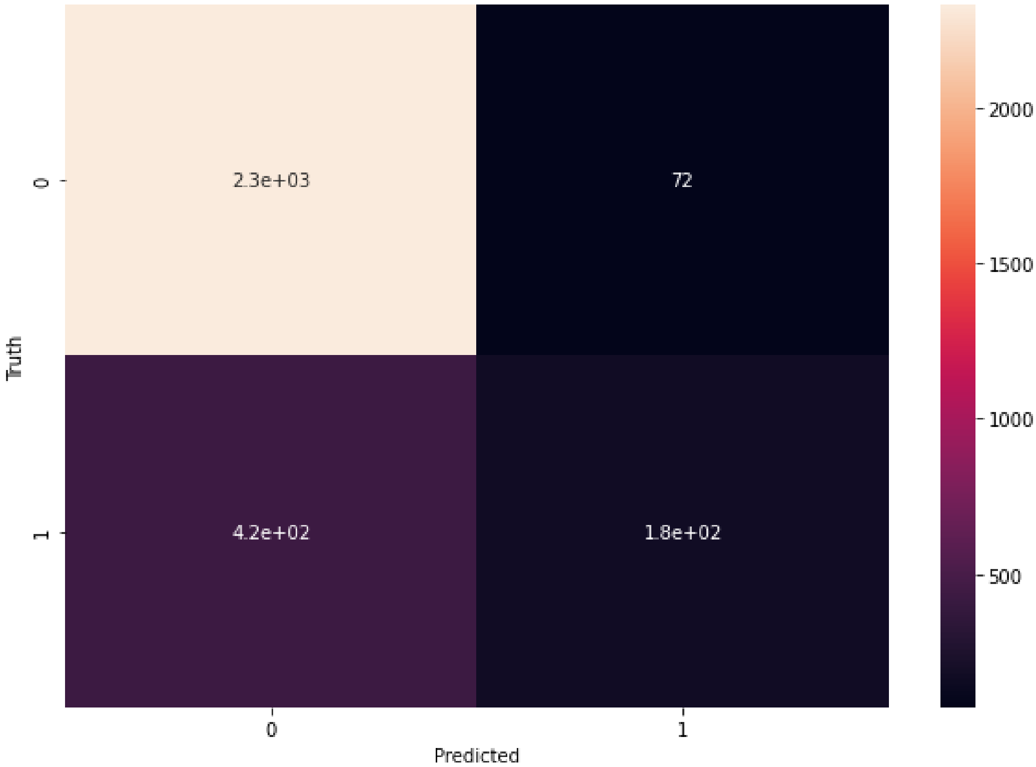
```
0.8343333333333334
```

In [98]:

```
plt.figure(figsize = (10,7))
sns.heatmap(cm,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[98]:

```
Text(69.0, 0.5, 'Truth')
```




In [100]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.97      0.90      2400
           1       0.71      0.29      0.41       600

    accuracy                           0.83      3000
   macro avg       0.78      0.63      0.66      3000
weighted avg       0.82      0.83      0.81      3000
```

In [ ]: