```
pip install --upgrade pip
```

Requirement already satisfied: pip in /usr/local/lib/python3.10/dist-packages (24.0)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system packa

import tensorflow as tf
print(tf.\_\_version\_\_)

2.15.0

## importing the libraries

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt

dataset = pd.read\_csv(('Churn\_Modelling.csv'))

## dataset

$\Rightarrow$	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsAc
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	
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	

10000 rows x 14 columns

x = dataset.iloc[:,3:13]
x

	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
9995	771	France	Male	39	5	0.00	2	1	0	96270.64
9996	516	France	Male	35	10	57369.61	1	1	1	101699.77
9997	709	France	Female	36	7	0.00	1	0	1	42085.58
9998	772	Germany	Male	42	3	75075.31	2	1	0	92888.52
9999	792	France	Female	28	4	130142.79	1	1	0	38190.78

10000 rows × 10 columns

```
y= dataset.iloc[:,13]
y
```

```
9995 0
9996 0
9997 1
9998 1
9999 0
Name: Exited, Length: 10000, dtype: int64
```

x.head()

	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

y.head()

Name: Exited, dtype: int64

## feature engineering

 $geography = pd.get\_dummies(x['Geography'], drop\_first = True)$ 

gender = pd.get\_dummies(x['Gender'],drop\_first = True)

x = x.drop(['Geography', 'Gender'], axis = 1)

x.head()

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

x = pd.concat([x,geography,gender],axis = 1)
x

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMeml
0	619	42	2	0.00	1	1	
1	608	41	1	83807.86	1	0	
2	502	42	8	159660.80	3	1	
3	699	39	1	0.00	2	0	
4	850	43	2	125510.82	1	1	
9995	771	39	5	0.00	2	1	
9996	516	35	10	57369.61	1	1	
9997	709	36	7	0.00	1	0	
9998	772	42	3	75075.31	2	1	
9999	792	28	4	130142.79	1	1	

10000 rows × 11 columns

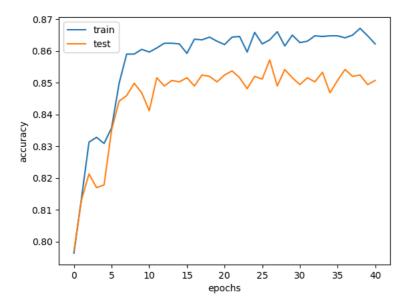
```
## splitting the data into training and testing
from sklearn.model selection import train test split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3, random_state = 0)
## feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
x train
     array([[-0.09792126, -0.55759842, -1.03635146, ..., -0.56987189,
               -0.5731713 , 0.92295821],
             [-1.12612023, \quad 0.01725942, \quad 0.69700901, \ \dots, \ -0.56987189,
             -0.5731713 , 0.92295821],
[-0.62230274, 3.5622161 ,
                                             0.00366482, \ldots, -0.56987189,
              -0.5731713 , -1.08347268],
             [\ 0.89943174,\ -0.36597914,\ \ 0.00366482,\ \ldots,\ -0.56987189,
             -0.5731713 , 0.92295821], [-0.62230274, -0.07855022,
                                             1.39035319, ..., -0.56987189,
                1.74467913, -1.08347268],
             [-0.28299708, 0.87954618, -1.38302356, ..., 1.75478035, -0.5731713 , -1.08347268]])
x_test
     array([[-0.55032881, -0.36597914, 1.0436811, ..., 1.75478035,
             -0.5731713 , -1.08347268],
[-1.31119605, 0.11306906, -1.03635146, ..., -0.56987189,
             -0.5731713 , -1.08347268],
[ 0.57040807,  0.30468834,  1.0436811 , ..., -0.56987189,  1.74467913, -1.08347268],
             [0.35448628, 0.11306906, -1.03635146, ..., -0.56987189,
             -0.5731713 , 0.92295821],
[ 0.42646021, 2.89154862, 1.73702529, ..., -0.56987189,
             -0.5731713 , 0.92295821],

[ 0.82745781 , 0.97535582 , -0.34300727 , ... , 1.75478035 ,
              -0.5731713 , -1.08347268]])
x_train.shape
     (7000, 11)
x test.shape
     (3000, 11)
## creating the ANN
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LeakyReLU, ReLU, ELU
from tensorflow.keras.layers import Dropout
classifier = Sequential()
Double-click (or enter) to edit
## adding inout layer
classifier.add(Dense(units=11,activation = 'relu'))
## adding the hidden layer1
classifier.add(Dense(units = 5, activation = 'relu', input_shape = (11,)))
## adding the hidden layer2
classifier.add(Dense(units = 2, activation = 'relu'))
```

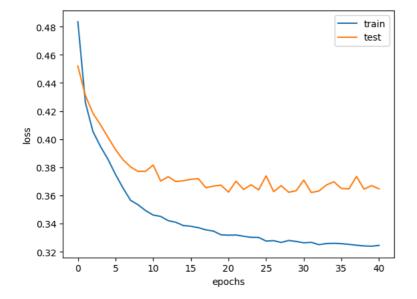
```
## adding the output layer
classifier.add(Dense(units = 1, activation = 'sigmoid'))
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics= ['accuracy'])
import tensorflow as tf
early_stopping = tf.keras.callbacks.EarlyStopping(
   monitor="val_loss",
   min_delta=0.001,
   patience=20,
   verbose=1.
   mode="auto"
   baseline=None,
   restore_best_weights=False,
   start_from_epoch=0,
model_history = classifier.fit(x_train,y_train, validation_split = 0.33, batch_size = 4, epochs = 100, callbacks = early_stc
   Epoch 1/100
   1173/1173 [================= ] - 4s 2ms/step - loss: 0.4835 - accuracy: 0.7963 - val_loss: 0.4520 - val_accu
   Epoch 2/100
   1173/1173 [=
                            Epoch 3/100
   1173/1173 [==
                     Epoch 4/100
   1173/1173 [=
                         =========] - 4s 3ms/step - loss: 0.3949 - accuracy: 0.8328 - val_loss: 0.4103 - val_accu
   Epoch 5/100
   Epoch 6/100
   Epoch 7/100
   1173/1173 [=:
                            :=======] - 3s 2ms/step - loss: 0.3652 - accuracy: 0.8499 - val_loss: 0.3854 - val_accu
   Epoch 8/100
   1173/1173 [===
                     Epoch 9/100
   1173/1173 [=:
                               ======] - 3s 2ms/step - loss: 0.3534 - accuracy: 0.8590 - val_loss: 0.3771 - val_accu
   Epoch 10/100
   1173/1173 [================== ] - 3s 2ms/step - loss: 0.3492 - accuracy: 0.8605 - val_loss: 0.3772 - val_accu
   Epoch 11/100
   1173/1173 [===:
                    Epoch 12/100
   Epoch 13/100
   1173/1173 [==
                        =============== ] - 3s 2ms/step - loss: 0.3421 - accuracy: 0.8624 - val_loss: 0.3734 - val_accu
   Epoch 14/100
   1173/1173 [==
                              :======] - 3s 2ms/step - loss: 0.3409 - accuracy: 0.8624 - val_loss: 0.3699 - val_accu
   Epoch 15/100
   1173/1173 [==
                                  :==] - 3s 2ms/step - loss: 0.3386 - accuracy: 0.8622 - val_loss: 0.3704 - val_accu
   Epoch 16/100
   1173/1173 [=
                                  ≔=l - 3s 2ms/step - loss: 0.3381 - accuracy: 0.8592 - val loss: 0.3715 - val accu
   Epoch 17/100
   1173/1173 [============== ] - 5s 4ms/step - loss: 0.3371 - accuracy: 0.8637 - val_loss: 0.3719 - val_accu
   Epoch 18/100
   1173/1173 [=
                                   ==] - 3s 2ms/step - loss: 0.3355 - accuracy: 0.8635 - val_loss: 0.3655 - val_accu
   Epoch 19/100
   1173/1173 [=====
                     ================= ] - 3s 2ms/step - loss: 0.3347 - accuracy: 0.8644 - val_loss: 0.3666 - val_accu
   Epoch 20/100
   1173/1173 [==
                                :=====] - 3s 2ms/step - loss: 0.3320 - accuracy: 0.8631 - val_loss: 0.3674 - val_accu
   Epoch 21/100
   1173/1173 [=
                                   ≔] - 4s 4ms/step - loss: 0.3318 - accuracy: 0.8620 - val loss: 0.3624 - val accu
   Epoch 22/100
   1173/1173 [==
                                   ==] - 3s 3ms/step - loss: 0.3319 - accuracy: 0.8644 - val loss: 0.3701 - val accu
   Epoch 23/100
                                =====] - 3s 3ms/step - loss: 0.3310 - accuracy: 0.8646 - val_loss: 0.3643 - val_accu
   1173/1173 [=:
   Epoch 24/100
   1173/1173 [==
                        =========] - 3s 3ms/step - loss: 0.3302 - accuracy: 0.8597 - val_loss: 0.3676 - val_accu
   Epoch 25/100
   1173/1173 [=:
                                =====] - 3s 2ms/step - loss: 0.3302 - accuracy: 0.8659 - val_loss: 0.3640 - val_accu
   Epoch 26/100
   1173/1173 [==
                            :=======] - 3s 2ms/step - loss: 0.3276 - accuracy: 0.8622 - val_loss: 0.3739 - val_accu
   Epoch 27/100
   1173/1173 [=:
                                   ==] - 3s 2ms/step - loss: 0.3279 - accuracy: 0.8635 - val loss: 0.3627 - val accu
   Epoch 28/100
   1173/1173 [==
                              Epoch 29/100
   1173/1173 [==
                            :=======] - 4s    3ms/step - loss: 0.3280 - accuracy: 0.8616 - val_loss: 0.3622 - val_accu
classifier.evaluate(x test,y test)
                                ≔] - 0s 1ms/step - loss: 0.3496 - accuracy: 0.8543
   [0.34959688782691956, 0.8543333411216736]
model_history.history.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
plt.plot(model_history.history['accuracy'])
plt.plot(model_history.history['val_accuracy'])
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend(['train','test'])
plt.show()
```



```
plt.plot(model_history.history['loss'])
plt.plot(model_history.history['val_loss'])
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend(['train','test'])
plt.show()
```



score = accuracy\_score(y\_test,y\_pred)
score

0.8543333333333333

Start coding or generate with AI.