```
import numpy as np
import pandas as pd
import tensorflow as tf

from google.colab import drive
drive.mount('/content/drive')

    Mounted at /content/drive

df = pd.read_csv("/content/Churn_Modelling.csv")

df.head()

    RowNumber CustomerId Surname Credi
```

	RowNumber	CustomerId	Surname	Credi
0	1	15634602	Hargrave	
1	2	15647311	Hill	
2	3	15619304	Onio	
3	4	15701354	Boni	
4	5	15737888	Mitchell	

```
# for X, take 4th column to untill last second column as independent variable and exited as dependent variable
X = df.iloc[:, 3:-1].values
y = df.iloc[:, -1].values
X
     array([[619, 'France', 'Female', ..., 1, 1, 101348.88],
             [608, 'Spain', 'Female', ..., 0, 1, 112542.58], [502, 'France', 'Female', ..., 1, 0, 113931.57],
             ...,
[709, 'France', 'Female', ..., 0, 1, 42085.58],
[772, 'Germany', 'Male', ..., 1, 0, 92888.52],
[792, 'France', 'Female', ..., 1, 0, 38190.78]], dtype=object)
У
     array([1, 0, 1, ..., 1, 1, 0])
#lebel encodding for gender column
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:, 2] = le.fit_transform(X[:, 2])
#one hot encoding for country column, for this first import all necesary moddule
#Then, define the transformer function which has list of transformer which transform value into one hot
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
#define column transfer function where instruct which column need to apply the function
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
#apply the CT to X
X = np.array(ct.fit_transform(X))
#feature scaling with std scaler
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)
Х
     array([[ 0.99720391, -0.57873591, -0.57380915, ..., 0.64609167,
             0.97024255, 0.02188649],
[-1.00280393, -0.57873591, 1.74273971, ..., -1.54776799,
```

Double-click (or enter) to edit

```
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Building **MNN**
                                           Building MNN
ann = tf.keras.models.Sequential()
#adding input layer
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
#adding hidden layer
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
# Adding the second hidden layer
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
# Adding the third hidden layer
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
# Adding the fourth hidden layer
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
#adding output laver
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

Adam stands for Adaptive Moment Estimation, and it's an extension of the stochastic gradient descent (SGD) algorithm. Adam adapts the learning rates of each parameter based on the past gradients and their squared gradients.

```
#compile the ANN
ann.compile(optimizer = 'adam', loss = 'binary crossentropy', metrics = ['accuracy'])
#training the ANN with training set with epoch 120
ann.fit(X_train, y_train, batch_size = 32, epochs = 120)
   Epoch 1/120
   235/235 [============] - 2s 2ms/step - loss: 0.5646 - accuracy:
   Epoch 2/120
   235/235 [===
                     ========] - 0s 2ms/step - loss: 0.4568 - accuracy:
   Epoch 3/120
   235/235 [============] - 0s 2ms/step - loss: 0.4362 - accuracy:
   Epoch 4/120
   235/235 [===
                     ========] - 0s 2ms/step - loss: 0.4252 - accuracy:
   Epoch 5/120
   235/235 [====
              Epoch 6/120
   235/235 [============] - 0s 2ms/step - loss: 0.4076 - accuracy:
   Epoch 7/120
   235/235 [============] - 0s 2ms/step - loss: 0.3996 - accuracy:
   Epoch 8/120
   235/235 [============] - 0s 2ms/step - loss: 0.3902 - accuracy:
   Epoch 9/120
   235/235 [===
                 Epoch 10/120
```

235/235 [===========] - 0s 2ms/step - loss: 0.3741 - accuracy:

#confusion matrix

[[1873 118] [243 26611

print(cm)

from sklearn.metrics import confusion_matrix cm = confusion_matrix(y_test, y_pred)

```
Epoch 11/120
   235/235 [===========] - 0s 2ms/step - loss: 0.3688 - accuracy:
   Epoch 12/120
   235/235 [=============] - 0s 2ms/step - loss: 0.3641 - accuracy:
   Epoch 13/120
                 ======== ] - 0s 2ms/step - loss: 0.3611 - accuracy:
   235/235 [====
   Epoch 14/120
   235/235 [============] - 0s 2ms/step - loss: 0.3586 - accuracy:
   Epoch 15/120
             235/235 [=====
   Epoch 16/120
   235/235 [=======] - 0s 2ms/step - loss: 0.3553 - accuracy:
   Epoch 17/120
   235/235 [==========] - 1s 2ms/step - loss: 0.3544 - accuracy:
   Epoch 18/120
   235/235 [======
              Epoch 19/120
   235/235 [====
            Epoch 20/120
   235/235 [=====
              Epoch 21/120
   235/235 [=======] - 1s 2ms/step - loss: 0.3500 - accuracy:
   Epoch 22/120
   235/235 [=====
              Epoch 23/120
   235/235 [=============] - 1s 3ms/step - loss: 0.3488 - accuracy:
   Epoch 24/120
   235/235 [=====
              Epoch 25/120
   235/235 [====
               ========= ] - 0s 2ms/step - loss: 0.3469 - accuracy:
   Epoch 26/120
               235/235 [=====
   Epoch 27/120
   235/235 [====
                 ========= | - 0s 2ms/step - loss: 0.3465 - accuracy:
   Epoch 28/120
   235/235 [===========] - 0s 2ms/step - loss: 0.3466 - accuracy:
   Epoch 29/120
   235/235 [====
            \# predict with x test and see the original y test and ypred line by line
y_pred = ann.predict(X_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
   79/79 г
                  ======= ] - 0s 2ms/step
   [[0 0]]
   [0 1]
   [0 0]
   [0 0]
   [0 0]
   [0 0]]
```

```
nobel barua
                                    :
Take 2 minute for epoch 120 and MNN
```

```
https://colab.research.google.com/drive/1aBWM9IyV7KSVldQdeFM8wfssbzZc0eOm\#scrollTo=SG3CZ\_sOdDSe\&printMode=true
```

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