```
!pip install numpy
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.26.
#Tensor Flow
import tensorflow as tf
import numpy as np
# Generate random input data
x = np.random.rand(100).astype(np.float32)
print("Input data (x):", x)
# Define the expected output (observed output)
y = x * 0.2 + 0.2
# Initialize weight and bias as TensorFlow variables
W = tf.Variable(tf.random.normal([1]), dtype=tf.float32)
b = tf.Variable(tf.zeros([1]), dtype=tf.float32)
# Define the mean squared error loss function
def mse loss():
   y pred = W * x + b
   loss = tf.reduce mean(tf.square(y pred - y))
   return loss
# Initialize the Adam optimizer
optimizer = tf.keras.optimizers.Adam()
for step in range(5000):
   with tf.GradientTape() as tape:
       # Record the forward pass to compute gradients
       loss = mse loss()
   # Compute gradients
   gradients = tape.gradient(loss, [W, b])
   # Update weights and bias using the optimizer
   optimizer.apply_gradients(zip(gradients, [W, b]))
   if step % 500 == 0:
       # Print current values of W, b, and loss
       current loss = mse loss().numpy()
       print(f"Step {step}: W = {W.numpy()}, b = {b.numpy()}, Loss = {current_loss}")
Fr Input data (x): [0.51037544 0.720212
                                        0.30098298 0.2948662 0.09435506 0.15432854
     0.75456876 0.56331754 0.6322214 0.81396973 0.08257426 0.6841585
     0.36965096 0.19662744 0.6770544 0.71373945 0.4826075 0.01518037
              0.16785221 0.63037205 0.6543851 0.55686384 0.17839725
     0.557871
     0.3379201 0.42592633 0.6293109 0.03527107 0.6165651 0.38065234
     0.18477175 0.87880427 0.5552781 0.84820366 0.3940719 0.06764966
     0.05110518 0.46766233 0.9527046 0.9039394 0.8361851 0.76819533
```

```
BIB01.ipynb - Colab
      0.32328105 0.97472024 0.58391833 0.19140992 0.40564215 0.41284883
      0.1519453 0.42220908 0.8389985 0.16241962 0.4154388 0.63810855
      0.6835967 0.08688549 0.77943367 0.4103383 0.1860193 0.9557191
      0.31993428 0.9631959 0.81115276 0.1627856 0.03839776 0.3139801
      0.00919499 0.04126265 0.21253552 0.41979152 0.99156904 0.9962813
      0.9720236 0.2531727 0.6337259 0.5880106 0.4540614 0.8828824
      0.55790275 0.3925333 0.5234228 0.97368306 0.6473126 0.44439787
      0.5885781 0.322056 0.9378256 0.40221557]
     Step 0: W = [-1.5380969], b = [0.00099999], Loss = 1.3232738971710205
     Step 500: W = [-1.1136128], b = [0.41038737], Loss = 0.3193606436252594
     Step 1000: W = [-0.8461263], b = [0.6120857], Loss = 0.09699486941099167
     Step 1500: W = [-0.68494165], b = [0.64349794], Loss = 0.06339596956968307
     Step 2000: W = [-0.5560062], b = [0.59637624], Loss = 0.04704602062702179
     Step 2500: W = [-0.42382202], b = [0.5282534], Loss = 0.03209450840950012
     Step 3000: W = [-0.28716764], b = [0.45614326], Loss = 0.01956496201455593
     Step 3500: W = [-0.15471043], b = [0.38633186], Loss = 0.010367147624492645
     Step 4000: W = [-0.03630579], b = [0.32404494], Loss = 0.00459934351965785
     Step 4500: W = [0.05957086], b = [0.2736821], Loss = 0.001623887219466269
#Keras
import numpy as np
from numpy import loadtxt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# Load data while skipping the header row
## INPUT Variables ##
# x1 - Number of times pregnant
# x2 - plasma glucose
# x3 - diastolic blood pressure
# x4 - Triceps skin fold thickness
# x5 - 2-hour serum insulin
# x6 - bmi
# x7 - diabetes pedigree function
# x8 - age (yrs)
## Output Variable ##
# Class Variable - 0 or 1
dataset = np.loadtxt('diabetes.csv', delimiter=',', skiprows=1)
```

dataset

```
\rightarrow  array([[ 6. , 148. , 72. , ..., 0.627, 50.
                                                     1.
                                                         ٦.
              , 85. , 66. , ..., 0.351, 31. ,
                                                     0.
                                                        1,
         [ 1.
               , 183. , 64.
                                     0.672, 32.
         [ 8.
                                                     1. ],
                              , ...,
              , 121. , 72.
                                     0.245, 30. ,
                                                     0.
                                                         1.
         [ 5.
                              , ...,
                , 126.
                      , 60.
                              , ..., 0.349, 47.
         Γ
           1.
                                                     1.
                                                         1,
         [ 1.
                , 93. , 70. , ...,
                                      0.315, 23. ,
                                                     0. 11)
```

```
# [:.:] - first : is range of rows and second : is columns
# [start:end] - begins at start, ends at end-1
x = dataset[:,0:8]
print(type(x))
print(x.shape)
print("\n")
v = dataset[:,8]
print(y)
→ <class 'numpy.ndarray'>
     (768, 8)
     [1. 0. 1. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1.
      1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0.
      1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0.
      1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0.
      0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0.
      1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.
      0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 1. 1. 0. 0.
      0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 1. 1. 0. 0.
      1. 1. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 1.
      1. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 0.
      0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0.
      1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 1.
      0. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0.
      1. 0. 1. 0. 0. 1. 0. 1. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0.
      0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 1. 1. 0. 1.
      1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0.
      0. 0. 1. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0. 1. 1. 0. 1. 0. 1. 0. 1. 0.
      1. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 1. 0. 0.
      0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1.
      0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0.
      1. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 0.
      0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
      0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 1. 1. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0.
      0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0.
      0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0.
      0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 0. 0. 0.
      0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1.
      1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 0. 0. 0. 0.
      0. 0. 0. 1. 1. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 1.
      1. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 1. 1. 0. 0. 1.
      0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 1. 1. 0. 0. 1.
      0. 0. 1. 0. 1. 1. 1. 0. 0. 1. 1. 1. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 0.]
# Step 2 - Creating or define the Keras Model
# Sequential Model
# Layer1 -> Layer2 -> Layer3
model = Sequential()
```

```
# The model expects row of data with 8 variables
# 12 = nodes
model.add(Dense(12, input shape=(8,), activation='relu'))
# Hidden Laver
#8 = nodes
model.add(Dense(8, activation='relu'))
# Output layer
model.add(Dense(1,activation='sigmoid'))
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning
       super(). init (activity regularizer=activity regularizer, **kwargs)
# Step 3 - Compile the Keras model
# loss (error)
# optimizer (adam)
# metrics = accuracy
model.compile(loss='binary crossentropy', optimizer='adam', metrics=['accuracy'])
#Step 4 - Fit / Train the model
#1 = Epochs - number of iterations / passes
#2 - Batch - sample data
model.fit(x,y, epochs=150, batch_size=10)
# Step 5 - evaluate the model
→ Epoch 1/150
     77/77 -
                              — 2s 2ms/step - accuracy: 0.3322 - loss: 11.2279
     Epoch 2/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.4156 - loss: 1.3248
     Epoch 3/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.5310 - loss: 0.8013
     Epoch 4/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.5742 - loss: 0.7500
     Epoch 5/150
     77/77 --
                               - 0s 2ms/step - accuracy: 0.6074 - loss: 0.7014
     Epoch 6/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6069 - loss: 0.6775
     Epoch 7/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6376 - loss: 0.6888
     Epoch 8/150
                               - 0s 2ms/step - accuracy: 0.6402 - loss: 0.6756
     77/77 -
     Epoch 9/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6251 - loss: 0.6861
     Epoch 10/150
     77/77 -
                              - 0s 2ms/step - accuracy: 0.6597 - loss: 0.6349
     Epoch 11/150
     77/77 -
                              — 0s 2ms/step - accuracy: 0.6682 - loss: 0.6370
     Epoch 12/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6940 - loss: 0.6085
     Epoch 13/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6594 - loss: 0.6303
     Epoch 14/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6727 - loss: 0.6065
     Epoch 15/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6732 - loss: 0.6099
     Epoch 16/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6661 - loss: 0.6028
     Epoch 17/150
```

```
77/77 -
                               - 0s 2ms/step - accuracy: 0.6889 - loss: 0.6085
     Epoch 18/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6864 - loss: 0.5805
     Epoch 19/150
     77/77 -
                               Os 2ms/step - accuracy: 0.6934 - loss: 0.5715
     Epoch 20/150
     77/77 ---
                               0s 2ms/step - accuracy: 0.6802 - loss: 0.5921
     Epoch 21/150
                               - 0s 2ms/step - accuracy: 0.6848 - loss: 0.5922
     77/77 -
     Epoch 22/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6927 - loss: 0.5956
     Epoch 23/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6832 - loss: 0.5877
     Epoch 24/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.6834 - loss: 0.5916
     Epoch 25/150
     77/77 --
                               Os 2ms/step - accuracy: 0.6640 - loss: 0.5884
     Epoch 26/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.7083 - loss: 0.5720
     Epoch 27/150
     77/77 -
                               - 0s 2ms/step - accuracy: 0.7008 - loss: 0.5807
     Epoch 28/150
     77/77 --
                               - 0s 2ms/step - accuracy: 0.6554 - loss: 0.6225
     Epoch 29/150
     77/77 -
                              — 0s 2ms/step - accuracy: 0.6809 - loss: 0.5923
model.evaluate(x,v)
<del>→</del> 24/24 -
                              - 0s 1ms/step - accuracy: 0.6723 - loss: 0.5510
     [0.5226908922195435, 0.7057291865348816]
#Theano
!pip install theano
→ Collecting theano
       Downloading Theano-1.0.5.tar.gz (2.8 MB)
                                                  - 2.8/2.8 MB 24.5 MB/s eta 0:00:00
       Preparing metadata (setup.py) ... done
     Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.10/dist-packages
     Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.10/dist-packages
     Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.10/dist-packages (
     Building wheels for collected packages: theano
       Building wheel for theano (setup.py) ... done
       Created wheel for theano: filename=Theano-1.0.5-py3-none-any.whl size=2668109 sha256
       Stored in directory: /root/.cache/pip/wheels/d9/e6/7d/2267d21a99e4ab8276f976f293b4ff
     Successfully built theano
     Installing collected packages: theano
     Successfully installed theano-1.0.5
import theano
from theano import *
import theano.tensor as T
import numpy as np
import pandas as pd
from theano import function
# scalar variables
v1 = T.dscalar()
v2 = T.scalar()
```

```
# subtraction
sres = v1-v2
#add
ares = v1+v2
#convert the results into functions
calcsres = theano.function([v1,v2],sres)
calcares = theano.function([v1,v2],ares)
calcares(12,23)
calcsres(13,12)
x = T.dmatrix('x')
y = T.dmatrix('y')
# addition
z = x+y
func = function([x,y],z)
m1 = \lceil
[1,2],
[3,4]
1
m2 = \Gamma
[4,5],
[6,7]
1
func(m1,m2)
# element wise sum
# 00 -> [1+4] -> 5
self.ctor = getattr(np, o_type.dtype)
     ______
    AttributeError
                                            Traceback (most recent call last)
    <ipython-input-18-8a274cf5f21f> in <cell line: 1>()
    ---> 1 import theano
          2 from theano import *
          3 import theano.tensor as T
          4 import numpy as np
          5 import pandas as pd
                                     8 frames -
    /usr/local/lib/python3.10/dist-packages/numpy/__init__.py in __getattr__(attr)
        322
        323
                   if attr in __former_attrs__:
                       raise AttributeError(__former_attrs__[attr])
    --> 324
        325
                   if attr == 'testing':
        326
    AttributeError: module 'numpy' has no attribute 'bool'.
    `np.bool` was a deprecated alias for the builtin `bool`. To avoid this error in
    existing code, use `bool` by itself. Doing this will not modify any behavior and is
    safe. If you specifically wanted the numpy scalar type, use `np.bool ` here.
    The aliases was originally deprecated in NumPy 1.20; for more details and guidance
    con the eniginal nelector note at-
                                                                                   Þ
```

8/26/24, 7:09 PM

```
### 2 - using numpy array
np_array = np.array(data)
x np = torch.from numpy(np array)
print(x np)
print(type(x np))
### 3 - using another tensor
x ones = torch.ones like(x data)
print("One Tensor: \n",x_ones)
x_rand = torch.rand_like(x_data,dtype=torch.float)
print(x rand)
#### more ways to create tensors
shape = (2,3)
random tensor = torch.rand(shape)
print(random tensor)
print(type(random tensor))
ones tensor = torch.ones(shape)
print(ones_tensor)
print(type(ones_tensor))
zeros tensor = torch.zeros(shape)
print(zeros tensor)
print(type(zeros_tensor))
tensor = torch.rand(3,4)
print(tensor)
tensor.shape
tensor.dtype
tensor.device
# Tensor Operations
if torch.cuda.is available():
    tensor = tensor.to('cuda')
    print("Device tensor is stored in ", tensor.device)
# Indexing, Slicing
tensor = torch.ones(4,4)
print(tensor)
print(tensor)
tensor1 = torch.zeros(4,4)
print(tensor1)
tensor2 = torch.cat([tensor,tensor1])
print(tensor2)
# Multiply Operation
tensor.mul(tensor1)
tensor * tensor1
tensor.T
# inplace - change the original tensor
tensor.add (3)
print(tensor)
# from tensor to numpy
t = torch.ones(5)
print(t)
n = t.numpy()
print(n)
print(type(n))
\rightarrow tensor([[1, 2],
             [3, 4]])
     <class 'torch.Tensor'>
```