

## Experiment 1: Build a Deep Neural Network Model Using Linear Regression with a Single Variable

**AIM:** To Build a Deep Neural Network Model Using Linear Regression with a Single Variable

### THEORY:

#### Regression:

A regression is a statistical technique that relates a dependent variable to one or more independent (explanatory) variables. A regression model is able to show whether changes observed in the dependent variable are associated with changes in one or more of the explanatory variables.

#### Linear Regression:

Linear regression is probably one of the most important and widely used regression techniques. It's among the simplest regression methods. One of its main advantages is the ease of interpreting results. When implementing linear regression of some dependent variable on the set of independent variables  $x = (x_1 \dots x_r)$ , where  $r$  is the number of predictors, you assume a linear relationship between  $y$  and  $x$ :  $y = \beta_0 + \beta_1 x_1 + \dots + \beta_r x_r + \epsilon$ . This equation is the regression equation.  $\beta_0, \beta_1, \beta_r$  are the regression coefficients, and  $\epsilon$  is the random error. Linear regression calculates the estimators of the regression coefficients or simply the predicted weights, denoted by  $b_1 \dots b_r$ . They define the estimated regression function  $f(x) = b_0 + b_1 x_1 + \dots + b_r x_r$ . This function should capture the dependencies between the inputs and output sufficiently well.

#### Simple Linear Regression:

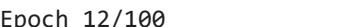
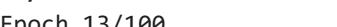
When implementing simple linear regression, with a given set of input-output ( $x-y$ ) pairs (green circles). Which are the observations. For example, the leftmost observation (green circle) has the input  $x=5$  and the actual output (response)  $y=5$ . The next one has  $x=15$  and  $y=20$ , and so on. The estimated regression function (black line) has the equation  $f(x) = b_0 + b_1 x$ . Your goal is to calculate the optimal values of the predicted weights  $b_0$  and  $b_1$  that minimize SSR and determine the estimated regression function. The value of  $b_0$ , also called the intercept, shows the point where the estimated regression line crosses the  $y$  axis. It is the value of the estimated response  $f(x)$  for  $x=0$ . The value of  $b_1$  determines the slope of the estimated regression line. The predicted responses (red squares) are the points on the regression line that correspond to the input values. For example, for the input  $x=5$ , the predicted response is  $f(5) = 8.33$  (represented with the leftmost red square). The residuals (vertical dashed gray lines) can be calculated as  $y_{1i} - f(x_{1i}) = y_{1i} - b_0 - b_1 x_{1i}$  for  $i=1$ .

```
1 # ===== STUDENT INFORMATION =====
2
3 STUDENT NAME = "A.Manas"
```

```
4 ROLL_NO = "23VE1A6601"
5 SECTION = "A"
6
7 EXPERIMENT_NO = "1"
8 EXPERIMENT_TITLE = "Design and Implementation of a Deep Neural Network Using Single Variable Linear Regression"
9
10 import uuid
11 SUBMISSION_ID = str(uuid.uuid4())[:8]
12
13 print("Student Name      :", STUDENT_NAME)
14 print("Roll Number       :", ROLL_NO)
15 print("Section          :", SECTION)
16 print("Experiment No    :", EXPERIMENT_NO)
17 print("Experiment Title : ", EXPERIMENT_TITLE)
18 print("Submission ID    :", SUBMISSION_ID)
19
20 # ====== EXPERIMENT CODE ======
21
22 import numpy as np
23 import matplotlib.pyplot as plt
24 import tensorflow as tf
25 observations=1000
26 xs=np.random.uniform(-10,10,(observations,1))
27 zs=np.random.uniform(-10,10,(observations,1))
28 generated_inputs=np.column_stack((xs,zs))
29 noise=np.random.uniform(-10,10,(observations,1))
30 generated_target=2*xs-3*zs+5+noise
31 np.savez('TF_intro',input=generated_inputs,targets=generated_target)
32 training_data=np.load('TF_intro.npz')
33 input_size=2
34 output_size=1
35 model = tf.keras.Sequential([tf.keras.layers.Dense(output_size)])
36 custom_optimizer=tf.keras.optimizers.SGD(learning_rate=0.02)
37 model.compile(optimizer=custom_optimizer,loss='mean_squared_error')
38 model.fit(training_data['input'],training_data['targets'],epochs=100,verbose=1)
39 model.layers[0].get_weights()
40 #[array([[ 1.3665189], [-3.1609795]], dtype=float32), array([4.9344487], dtype=float32)]
41 weights=model.layers[0].get_weights()[0]
42 bias=model.layers[0].get_weights()[1]
43 out=training_data['targets'].round(1)
44 from sklearn.metrics import mean_squared_error
45 mse = mean_squared_error(generated_target, out)
```

```
46 rmse = np.sqrt(mse)
47 print("RMSE:", rmse)
48 plt.scatter(np.squeeze(model.predict_on_batch(training_data['input'])),np.squeeze(training_data['targets']),c='#88c999')
49 plt.xlabel('Input')
50 plt.ylabel('Predicted Output')
51 plt.show()
```



Student Name : A.Manas  
Roll Number : 23VE1A6601  
Section : A  
Experiment No : 1  
Experiment Title : Design and Implementation of a Deep Neural Network Using Single Variable Linear Regression  
Submission ID : f55c2418  
Epoch 1/100  
**32/32**  0s 2ms/step - loss: 238.3133  
Epoch 2/100  
**32/32**  0s 2ms/step - loss: 52.6434  
Epoch 3/100  
**32/32**  0s 2ms/step - loss: 44.3211  
Epoch 4/100  
**32/32**  0s 2ms/step - loss: 40.9329  
Epoch 5/100  
**32/32**  0s 2ms/step - loss: 40.8272  
Epoch 6/100  
**32/32**  0s 2ms/step - loss: 46.6195  
Epoch 7/100  
**32/32**  0s 2ms/step - loss: 36.4272  
Epoch 8/100  
**32/32**  0s 3ms/step - loss: 41.3001  
Epoch 9/100  
**32/32**  0s 2ms/step - loss: 42.5544  
Epoch 10/100  
**32/32**  0s 2ms/step - loss: 36.3560  
Epoch 11/100  
**32/32**  0s 2ms/step - loss: 46.5068  
Epoch 12/100  
**32/32**  0s 2ms/step - loss: 37.8015  
Epoch 13/100  
**32/32**  0s 2ms/step - loss: 36.2086  
Epoch 14/100  
**32/32**  0s 2ms/step - loss: 39.9005  
Epoch 15/100  
**32/32**  0s 2ms/step - loss: 38.0008  
Epoch 16/100  
**32/32**  0s 2ms/step - loss: 39.2541  
Epoch 17/100  
**32/32**  0s 2ms/step - loss: 47.5368  
Epoch 18/100  
**32/32**  0s 2ms/step - loss: 39.2756  
Epoch 19/100  
**32/32**  0s 2ms/step - loss: 49.1476  
Epoch 20/100  
**32/32**  0s 2ms/step - loss: 42.6022

```
--, --          0s 2ms/step - loss: 42.0022
Epoch 21/100
32/32 0s 2ms/step - loss: 45.3735
Epoch 22/100
32/32 0s 2ms/step - loss: 35.9806
Epoch 23/100
32/32 0s 2ms/step - loss: 42.5034
Epoch 24/100
32/32 0s 2ms/step - loss: 44.0267
Epoch 25/100
32/32 0s 2ms/step - loss: 37.7841
Epoch 26/100
32/32 0s 2ms/step - loss: 40.1876
Epoch 27/100
32/32 0s 2ms/step - loss: 41.3214
Epoch 28/100
32/32 0s 2ms/step - loss: 46.7956
Epoch 29/100
32/32 0s 2ms/step - loss: 41.3469
Epoch 30/100
32/32 0s 2ms/step - loss: 38.4778
Epoch 31/100
32/32 0s 2ms/step - loss: 45.9277
Epoch 32/100
32/32 0s 2ms/step - loss: 46.4293
Epoch 33/100
32/32 0s 2ms/step - loss: 38.2542
Epoch 34/100
32/32 0s 2ms/step - loss: 39.7503
Epoch 35/100
32/32 0s 2ms/step - loss: 56.0627
Epoch 36/100
32/32 0s 2ms/step - loss: 38.9679
Epoch 37/100
32/32 0s 2ms/step - loss: 39.5688
Epoch 38/100
32/32 0s 2ms/step - loss: 41.8502
Epoch 39/100
32/32 0s 2ms/step - loss: 44.9113
Epoch 40/100
32/32 0s 2ms/step - loss: 42.4070
Epoch 41/100
32/32 0s 2ms/step - loss: 38.7285
Epoch 42/100
32/32 0s 3ms/step - loss: 42.8847
Epoch 43/100
32/32 0s 2ms/step - loss: 33.9196
```

```
--, --          -- 2ms/step - loss: 41.2457
Epoch 44/100
32/32 0s 2ms/step - loss: 41.2457
Epoch 45/100
32/32 0s 2ms/step - loss: 43.0544
Epoch 46/100
32/32 0s 2ms/step - loss: 38.2692
Epoch 47/100
32/32 0s 2ms/step - loss: 44.7310
Epoch 48/100
32/32 0s 2ms/step - loss: 38.4734
Epoch 49/100
32/32 0s 2ms/step - loss: 38.4081
Epoch 50/100
32/32 0s 2ms/step - loss: 41.4418
Epoch 51/100
32/32 0s 2ms/step - loss: 38.6013
Epoch 52/100
32/32 0s 2ms/step - loss: 42.7128
Epoch 53/100
32/32 0s 3ms/step - loss: 49.4060
Epoch 54/100
32/32 0s 2ms/step - loss: 34.9074
Epoch 55/100
32/32 0s 2ms/step - loss: 39.6249
Epoch 56/100
32/32 0s 2ms/step - loss: 39.1805
Epoch 57/100
32/32 0s 2ms/step - loss: 48.5686
Epoch 58/100
32/32 0s 2ms/step - loss: 40.7187
Epoch 59/100
32/32 0s 2ms/step - loss: 47.6340
Epoch 60/100
32/32 0s 2ms/step - loss: 39.8497
Epoch 61/100
32/32 0s 3ms/step - loss: 41.8874
Epoch 62/100
32/32 0s 4ms/step - loss: 41.3884
Epoch 63/100
32/32 0s 3ms/step - loss: 49.3072
Epoch 64/100
32/32 0s 4ms/step - loss: 37.9595
Epoch 65/100
32/32 0s 4ms/step - loss: 38.7266
Epoch 66/100
32/32 0s 3ms/step - loss: 36.7106
```

```
--, --  
Epoch 67/100  
32/32 0s 3ms/step - loss: 40.0880  
Epoch 68/100  
32/32 0s 3ms/step - loss: 42.4366  
Epoch 69/100  
32/32 0s 4ms/step - loss: 40.6139  
Epoch 70/100  
32/32 0s 4ms/step - loss: 41.1537  
Epoch 71/100  
32/32 0s 3ms/step - loss: 41.3927  
Epoch 72/100  
32/32 0s 4ms/step - loss: 45.1802  
Epoch 73/100  
32/32 0s 3ms/step - loss: 50.4067  
Epoch 74/100  
32/32 0s 2ms/step - loss: 45.5519  
Epoch 75/100  
32/32 0s 2ms/step - loss: 37.8879  
Epoch 76/100  
32/32 0s 2ms/step - loss: 37.0334  
Epoch 77/100  
32/32 0s 2ms/step - loss: 41.0297  
Epoch 78/100  
32/32 0s 2ms/step - loss: 48.5693  
Epoch 79/100  
32/32 0s 2ms/step - loss: 37.1003  
Epoch 80/100  
32/32 0s 2ms/step - loss: 38.6024  
Epoch 81/100  
32/32 0s 2ms/step - loss: 34.2116  
Epoch 82/100  
32/32 0s 2ms/step - loss: 36.5214  
Epoch 83/100  
32/32 0s 2ms/step - loss: 39.8677  
Epoch 84/100  
32/32 0s 2ms/step - loss: 37.2829  
Epoch 85/100  
32/32 0s 2ms/step - loss: 37.5172  
Epoch 86/100  
32/32 0s 2ms/step - loss: 37.1776  
Epoch 87/100  
32/32 0s 2ms/step - loss: 47.3886  
Epoch 88/100  
32/32 0s 2ms/step - loss: 34.8500  
Epoch 89/100  
32/32 0s 2ms/step - loss: 37.1187
```

```
Epoch 90/100  
32/32 0s 2ms/step - loss: 42.8309  
Epoch 91/100  
32/32 0s 2ms/step - loss: 39.1998  
Epoch 92/100  
32/32 0s 2ms/step - loss: 38.3145  
Epoch 93/100  
32/32 0s 2ms/step - loss: 38.5572  
Epoch 94/100  
32/32 0s 2ms/step - loss: 44.8120  
Epoch 95/100  
32/32 0s 2ms/step - loss: 48.4656  
Epoch 96/100  
32/32 0s 2ms/step - loss: 36.3916  
Epoch 97/100  
32/32 0s 2ms/step - loss: 42.7927  
Epoch 98/100  
32/32 0s 2ms/step - loss: 42.7941  
Epoch 99/100  
32/32 0s 2ms/step - loss: 39.1964  
Epoch 100/100  
32/32 0s 2ms/step - loss: 39.3827  
RMSE: 0.02862285600991514
```

