


Name: Saniya Mansuri Rollno: 20CO071

1] Linear regression by using Deep Neural network: Implement Boston housing price prediction problem by Linear regression using Deep Neural network. Use Boston House price prediction dataset

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
# Preprocessing and evaluation
from sklearn.model_selection import train_test_split
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import MinMaxScaler

(X_train , y_train), (X_test , y_test) = tf.keras.datasets.boston_housing.load_data(
    path = 'boston_housing_npz',
    test_split = 0.2,
    seed = 42
)
```

 Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/boston_housing_npz_57026/57026 [=====] - 0s 0us/step

```
(X_train.shape, type(X_train)), (X_test.shape, type(X_test)), (y_train.shape, type(y_train)), (y_test.shape, type(y_test))
```

```
((404, 13), numpy.ndarray),
((102, 13), numpy.ndarray),
((404,), numpy.ndarray),
((102,), numpy.ndarray))
```

```
# Converting Data to DataFrame
X_train_df = pd.DataFrame(X_train)
y_train_df = pd.DataFrame(y_train)
# Preview the training data
X_train_df.head(10)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.09178	0.0	4.05	0.0	0.510	6.416	84.1	2.6463	5.0	296.0	16.6	395.50	9.04
1	0.05644	40.0	6.41	1.0	0.447	6.758	32.9	4.0776	4.0	254.0	17.6	396.90	3.53
2	0.10574	0.0	27.74	0.0	0.609	5.983	98.8	1.8681	4.0	711.0	20.1	390.11	18.07
3	0.09164	0.0	10.81	0.0	0.413	6.065	7.8	5.2873	4.0	305.0	19.2	390.91	5.52
4	5.09017	0.0	18.10	0.0	0.713	6.297	91.8	2.3682	24.0	666.0	20.2	385.09	17.27
5	0.10153	0.0	12.83	0.0	0.437	6.279	74.5	4.0522	5.0	398.0	18.7	373.66	11.97
6	0.31827	0.0	9.90	0.0	0.544	5.914	83.2	3.9986	4.0	304.0	18.4	390.70	18.33
7	0.29090	0.0	21.89	0.0	0.624	6.174	93.6	1.6119	4.0	437.0	21.2	388.08	24.16
8	4.03841	0.0	18.10	0.0	0.532	6.229	90.7	3.0993	24.0	666.0	20.2	395.33	12.87
9	0.22438	0.0	9.69	0.0	0.585	6.027	79.7	2.4982	6.0	391.0	19.2	396.90	14.33

```
X_train_df.info()
print('_'*40)
y_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404 entries, 0 to 403
Data columns (total 13 columns):
#   Column   Non-Null Count  Dtype
---  -
0    0         404 non-null    float64
1    1         404 non-null    float64
2    2         404 non-null    float64
3    3         404 non-null    float64
```

```
4 4 404 non-null float64
5 5 404 non-null float64
6 6 404 non-null float64
7 7 404 non-null float64
8 8 404 non-null float64
9 9 404 non-null float64
10 10 404 non-null float64
11 11 404 non-null float64
12 12 404 non-null float64
dtypes: float64(13)
memory usage: 41.2 KB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404 entries, 0 to 403
Data columns (total 1 columns):
#   Column  Non-Null Count  Dtype
---  -
0     0    404 non-null    float64
dtypes: float64(1)
memory usage: 3.3 KB
```

X_train_df.describe()

	0	1	2	3	4	5	6	7	8	9	10	
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000
mean	3.789989	11.568069	11.214059	0.069307	0.554524	6.284824	69.119307	3.792258	9.660891	408.960396	18.481931	35.789989
std	9.132761	24.269648	6.925462	0.254290	0.116408	0.723759	28.034606	2.142651	8.736073	169.685166	2.157322	9.132761
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.137000	1.000000	187.000000	12.600000	0.006320
25%	0.081960	0.000000	5.190000	0.000000	0.452000	5.878750	45.475000	2.097050	4.000000	281.000000	17.400000	37.500000
50%	0.262660	0.000000	9.690000	0.000000	0.538000	6.210000	77.500000	3.167500	5.000000	330.000000	19.100000	39.000000
75%	3.717875	12.500000	18.100000	0.000000	0.624000	6.620500	94.425000	5.118000	24.000000	666.000000	20.200000	39.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	39.000000

```
# Create column transformer
ct = make_column_transformer(
    (MinMaxScaler(), [0, 1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12])
)
# Normalization and data type change
X_train = ct.fit_transform(X_train).astype('float32')
X_test = ct.transform(X_test).astype('float32')
y_train = y_train.astype('float32')
y_test = y_test.astype('float32')
# Distribution of X_train feature values after normalization
pd.DataFrame(X_train).describe()
```

	0	1	2	3	4	5	6	7	8	9	10	
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000
mean	0.042528	0.115681	0.394210	0.348815	0.521905	0.681970	0.241618	0.376560	0.423589	0.625737	0.897607	0.042528
std	0.102650	0.242696	0.253866	0.239522	0.138678	0.288719	0.194973	0.379829	0.323827	0.229502	0.232131	0.102650
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000850	0.000000	0.173387	0.137860	0.444098	0.438466	0.087361	0.130435	0.179389	0.510638	0.944992	0.000850
50%	0.002881	0.000000	0.338343	0.314815	0.507569	0.768280	0.184767	0.173913	0.272901	0.691489	0.985892	0.002881
75%	0.041717	0.125000	0.646628	0.491770	0.586223	0.942585	0.362255	1.000000	0.914122	0.808511	0.997252	0.041717
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

```
# Reserve data for validation
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.1, random_state=42)
X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

((363, 12), (41, 12), (363,), (41,))

```

# Set random seed
tf.random.set_seed(42)
# Building the model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(units=10, activation='relu', input_shape=(X_train.shape[1],), name='Dense_1'),
    tf.keras.layers.Dense(units=100, activation='relu', name='Dense_2'),
    tf.keras.layers.Dense(units=1, name='Prediction')
])
# Compiling the model
model.compile(
    loss = tf.keras.losses.mean_squared_error,
    optimizer = tf.keras.optimizers.RMSprop(learning_rate=0.01),
    metrics = ['mse']
)
# Training the model
history = model.fit(
    X_train,
    y_train,
    batch_size=32,
    epochs=50,
    validation_data=(X_val, y_val)
)

Epoch 1/50
12/12 [=====] - 1s 34ms/step - loss: 262.2998 - mse: 262.2998 - val_loss: 123.0861 - val_mse: 123.0861
Epoch 2/50
12/12 [=====] - 0s 7ms/step - loss: 85.5223 - mse: 85.5223 - val_loss: 95.9422 - val_mse: 95.9422
Epoch 3/50
12/12 [=====] - 0s 6ms/step - loss: 67.6636 - mse: 67.6636 - val_loss: 76.0641 - val_mse: 76.0641
Epoch 4/50
12/12 [=====] - 0s 8ms/step - loss: 55.3887 - mse: 55.3887 - val_loss: 65.2183 - val_mse: 65.2183
Epoch 5/50
12/12 [=====] - 0s 5ms/step - loss: 51.4000 - mse: 51.4000 - val_loss: 84.0909 - val_mse: 84.0909
Epoch 6/50
12/12 [=====] - 0s 5ms/step - loss: 41.6997 - mse: 41.6997 - val_loss: 79.2245 - val_mse: 79.2245
Epoch 7/50
12/12 [=====] - 0s 7ms/step - loss: 35.1139 - mse: 35.1139 - val_loss: 39.8358 - val_mse: 39.8358
Epoch 8/50
12/12 [=====] - 0s 7ms/step - loss: 31.3163 - mse: 31.3163 - val_loss: 68.5040 - val_mse: 68.5040
Epoch 9/50
12/12 [=====] - 0s 6ms/step - loss: 29.7963 - mse: 29.7963 - val_loss: 37.0860 - val_mse: 37.0860
Epoch 10/50
12/12 [=====] - 0s 6ms/step - loss: 33.2242 - mse: 33.2242 - val_loss: 53.0522 - val_mse: 53.0522
Epoch 11/50
12/12 [=====] - 0s 7ms/step - loss: 25.5464 - mse: 25.5464 - val_loss: 50.9062 - val_mse: 50.9062
Epoch 12/50
12/12 [=====] - 0s 6ms/step - loss: 31.0931 - mse: 31.0931 - val_loss: 29.5716 - val_mse: 29.5716
Epoch 13/50
12/12 [=====] - 0s 5ms/step - loss: 24.8692 - mse: 24.8692 - val_loss: 51.1461 - val_mse: 51.1461
Epoch 14/50
12/12 [=====] - 0s 7ms/step - loss: 27.6374 - mse: 27.6374 - val_loss: 23.7920 - val_mse: 23.7920
Epoch 15/50
12/12 [=====] - 0s 5ms/step - loss: 26.3090 - mse: 26.3090 - val_loss: 26.7212 - val_mse: 26.7212
Epoch 16/50
12/12 [=====] - 0s 5ms/step - loss: 23.9364 - mse: 23.9364 - val_loss: 24.4725 - val_mse: 24.4725
Epoch 17/50
12/12 [=====] - 0s 5ms/step - loss: 24.7855 - mse: 24.7855 - val_loss: 47.6823 - val_mse: 47.6823
Epoch 18/50
12/12 [=====] - 0s 5ms/step - loss: 24.9524 - mse: 24.9524 - val_loss: 22.4379 - val_mse: 22.4379
Epoch 19/50
12/12 [=====] - 0s 6ms/step - loss: 20.7859 - mse: 20.7859 - val_loss: 19.8567 - val_mse: 19.8567
Epoch 20/50
12/12 [=====] - 0s 6ms/step - loss: 23.9060 - mse: 23.9060 - val_loss: 26.2613 - val_mse: 26.2613
Epoch 21/50
12/12 [=====] - 0s 5ms/step - loss: 22.9522 - mse: 22.9522 - val_loss: 19.1431 - val_mse: 19.1431
Epoch 22/50
12/12 [=====] - 0s 5ms/step - loss: 18.6399 - mse: 18.6399 - val_loss: 70.5777 - val_mse: 70.5777
Epoch 23/50
12/12 [=====] - 0s 6ms/step - loss: 22.0048 - mse: 22.0048 - val_loss: 17.6851 - val_mse: 17.6851
Epoch 24/50
12/12 [=====] - 0s 7ms/step - loss: 20.9056 - mse: 20.9056 - val_loss: 16.6789 - val_mse: 16.6789
Epoch 25/50
12/12 [=====] - 0s 6ms/step - loss: 18.0682 - mse: 18.0682 - val_loss: 46.4670 - val_mse: 46.4670
Epoch 26/50
12/12 [=====] - 0s 6ms/step - loss: 20.2548 - mse: 20.2548 - val_loss: 46.9747 - val_mse: 46.9747
Epoch 27/50
12/12 [=====] - 0s 5ms/step - loss: 17.4214 - mse: 17.4214 - val_loss: 32.7998 - val_mse: 32.7998
Epoch 28/50
12/12 [=====] - 0s 7ms/step - loss: 17.8515 - mse: 17.8515 - val_loss: 19.5631 - val_mse: 19.5631

```

Epoch 29/50

12/12 [=====] - 0s 5ms/step - loss: 20.3100 - mse: 20.3100 - val_loss: 20.7227 - val_mse: 20.7227

y_train.mean(), y_val.mean()

(22.235537, 24.89756)

print("Evaluation on Test data \n")

loss, mse = model.evaluate(X_test, y_test, batch_size=32)

print(f"\nModel loss on test set: {loss}")

print(f"Model mean squared error on test set: {(mse):.2f}")

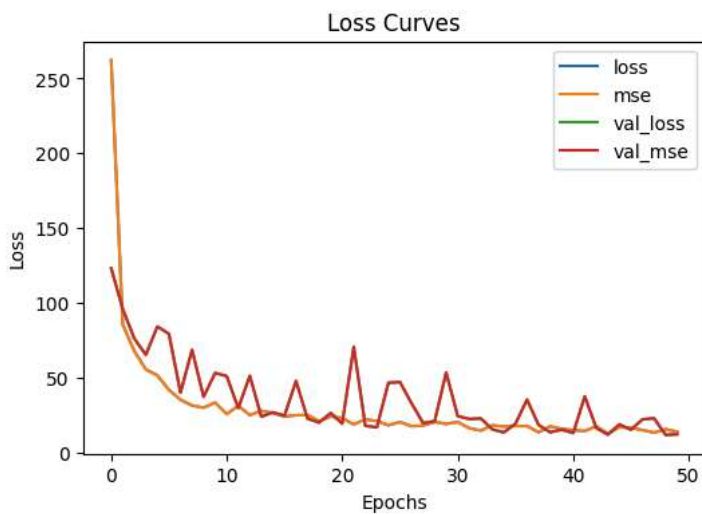
Evaluation on Test data

4/4 [=====] - 0s 10ms/step - loss: 15.4817 - mse: 15.4817

Model loss on test set: 15.481749534606934

Model mean squared error on test set: 15.48

```
pd.DataFrame(history.history).plot(figsize=(6, 4), xlabel="Epochs", ylabel="Loss", title='Loss Curves')
plt.show()
```



Make predictions

y_pred = model.predict(X_test)

View the first prediction

y_pred[0]

4/4 [=====] - 0s 3ms/step

array([20.61844], dtype=float32)