dlprac1

February 17, 2024

1 Practical 1:- Implement Boston housing price predictionproblem by Linear regression using Deep Neural network. Use Boston House price prediction dataset.

```
[8]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from sklearn.metrics import accuracy_score
```

2 Loading the inbuilt dataset

```
[2]: boston = load_boston()
data = pd.DataFrame(boston.data, columns=boston.feature_names)
data['PRICE'] = boston.target

# Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(data.iloc[:, :-1], data.

→iloc[:, -1], test_size=0.2, random_state=42)
```

D:\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function load_boston is deprecated; `load_boston` is deprecated in 1.0 and will be removed in 1.2.

The Boston housing prices dataset has an ethical problem. You can refer to the documentation of this function for further details.

The scikit-learn maintainers therefore strongly discourage the use of this dataset unless the purpose of the code is to study and educate about ethical issues in data science and machine learning.

In this special case, you can fetch the dataset from the original source::

```
import pandas as pd
      import numpy as np
      data_url = "http://lib.stat.cmu.edu/datasets/boston"
      raw df = pd.read csv(data url, sep="\s+", skiprows=22, header=None)
      data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
      target = raw_df.values[1::2, 2]
  Alternative datasets include the California housing dataset (i.e.
  :func:`~sklearn.datasets.fetch california housing`) and the Ames housing
  dataset. You can load the datasets as follows::
      from sklearn.datasets import fetch_california_housing
      housing = fetch_california_housing()
 for the California housing dataset and::
      from sklearn.datasets import fetch openml
      housing = fetch_openml(name="house_prices", as_frame=True)
 for the Ames housing dataset.
warnings.warn(msg, category=FutureWarning)
```

3 Standardizes the features

```
[3]: scaler = StandardScaler()
X_train = scaler.fit_transform(X_traina)
X_test = scaler.transform(X_test)
```

4 Defines a neural network model with three layers (Dense layers with ReLU activation). Compiles the model using mean squared error (mse) as the loss function.

[5]: # Train the model history = model.fit(X_train, y_train, epochs=100, batch_size=32, □ validation_split=0.2)

```
Epoch 1/100
val_loss: 529.2634
Epoch 2/100
val_loss: 499.8468
Epoch 3/100
val loss: 464.2322
Epoch 4/100
val loss: 418.8820
Epoch 5/100
val_loss: 359.3557
Epoch 6/100
val_loss: 287.9466
Epoch 7/100
val_loss: 213.2249
Epoch 8/100
val loss: 148.4100
Epoch 9/100
val loss: 101.0766
Epoch 10/100
val_loss: 72.2913
Epoch 11/100
54.2463
Epoch 12/100
val_loss: 43.5660
Epoch 13/100
36.8523
Epoch 14/100
33.0155
Epoch 15/100
```

```
31.2338
Epoch 16/100
30.0956
Epoch 17/100
val_loss: 29.5187
Epoch 18/100
29.2508
Epoch 19/100
28.9362
Epoch 20/100
val_loss: 28.6153
Epoch 21/100
val loss: 28.3776
Epoch 22/100
val_loss: 27.9476
Epoch 23/100
val_loss: 27.3070
Epoch 24/100
val_loss: 26.5387
Epoch 25/100
val_loss: 26.0835
Epoch 26/100
val loss: 25.6259
Epoch 27/100
val_loss: 25.0388
Epoch 28/100
25.3922
Epoch 29/100
25.0191
Epoch 30/100
val_loss: 24.5823
Epoch 31/100
```

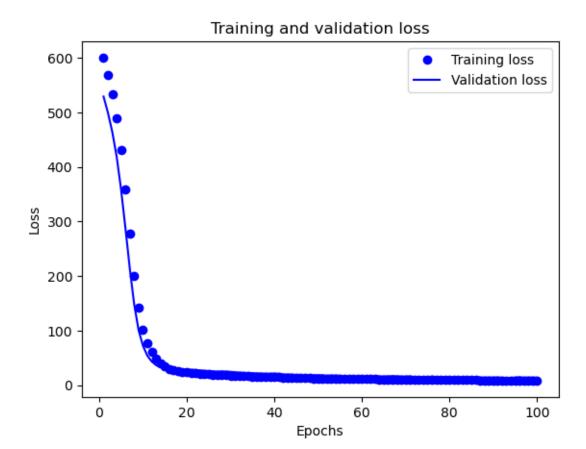
```
23.8763
Epoch 32/100
23.2500
Epoch 33/100
22.7492
Epoch 34/100
22.4657
Epoch 35/100
val_loss: 22.2116
Epoch 36/100
val_loss: 21.7548
Epoch 37/100
val loss: 21.5348
Epoch 38/100
val_loss: 21.2313
Epoch 39/100
val_loss: 21.1763
Epoch 40/100
11/11 [=========== ] - Os 15ms/step - loss: 14.5744 -
val_loss: 21.3975
Epoch 41/100
val_loss: 21.0292
Epoch 42/100
val loss: 19.8887
Epoch 43/100
val_loss: 19.7550
Epoch 44/100
val_loss: 19.5154
Epoch 45/100
val_loss: 19.0022
Epoch 46/100
val_loss: 18.8534
Epoch 47/100
```

```
18.8116
Epoch 48/100
18.7257
Epoch 49/100
val_loss: 18.5245
Epoch 50/100
val_loss: 18.4571
Epoch 51/100
18.3556
Epoch 52/100
val_loss: 17.4214
Epoch 53/100
val loss: 17.9152
Epoch 54/100
val_loss: 17.8312
Epoch 55/100
17.3287
Epoch 56/100
16.8679
Epoch 57/100
val_loss: 16.8250
Epoch 58/100
val loss: 16.6181
Epoch 59/100
val_loss: 16.3434
Epoch 60/100
val_loss: 16.4792
Epoch 61/100
val_loss: 16.5548
Epoch 62/100
17.0604
Epoch 63/100
```

```
val_loss: 16.9950
Epoch 64/100
16.2817
Epoch 65/100
16.2099
Epoch 66/100
val_loss: 16.3938
Epoch 67/100
val_loss: 16.7752
Epoch 68/100
val_loss: 16.5071
Epoch 69/100
val loss: 15.9741
Epoch 70/100
16.0716
Epoch 71/100
16.3042
Epoch 72/100
15.0136
Epoch 73/100
14.9351
Epoch 74/100
14.9469
Epoch 75/100
15.2001
Epoch 76/100
15.8626
Epoch 77/100
15.1977
Epoch 78/100
14.9133
Epoch 79/100
```

```
15.1582
Epoch 80/100
15.1670
Epoch 81/100
14.5944
Epoch 82/100
14.1969
Epoch 83/100
13.8138
Epoch 84/100
13.9418
Epoch 85/100
14.6091
Epoch 86/100
14.6034
Epoch 87/100
14.3042
Epoch 88/100
14.2241
Epoch 89/100
14.2032
Epoch 90/100
14.2421
Epoch 91/100
14.3701
Epoch 92/100
14.0006
Epoch 93/100
13.1046
Epoch 94/100
13.4923
Epoch 95/100
```

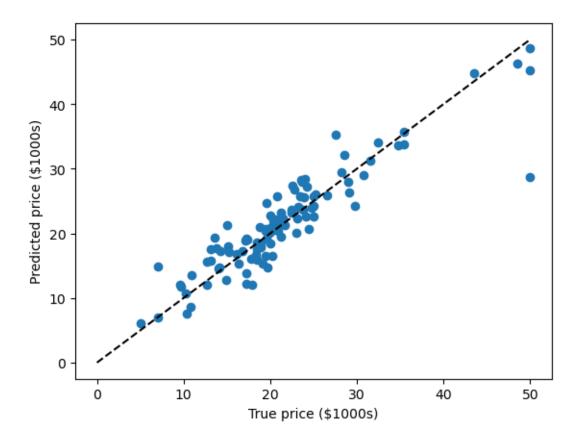
```
14.1478
  Epoch 96/100
  14.7744
  Epoch 97/100
  13.9084
  Epoch 98/100
               =========] - Os 15ms/step - loss: 8.5641 - val_loss:
  11/11 [=======
  14.1686
  Epoch 99/100
  14.2366
  Epoch 100/100
  13.7527
[6]: # Evaluate the model
  model.evaluate(X_test, y_test)
  [6]: 12.21752643585205
[9]: # Visualize the training history
  loss = history.history['loss']
  val_loss = history.history['val_loss']
  epochs = range(1, len(loss) + 1)
  plt.plot(epochs, loss, 'bo', label='Training loss')
  plt.plot(epochs, val_loss, 'b', label='Validation loss')
  plt.title('Training and validation loss')
  plt.xlabel('Epochs')
  plt.ylabel('Loss')
  plt.legend()
  plt.show()
```



```
[10]: # Visualize the linear regression graph
y_pred = model.predict(X_test)

plt.scatter(y_test, y_pred)
plt.plot([0, 50], [0, 50], '--k')
plt.axis('tight')
plt.xlabel('True price ($1000s)')
plt.ylabel('Predicted price ($1000s)')
plt.show()
```

4/4 [=======] - 1s 6ms/step



5 Checking for Custom Input

D:\Anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names warnings.warn(