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- ## DSC 650 - Assignment 5.3 - Tensorflow Keras Regression Example

https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/chapter04_getting-started-with-neural-networks.ipynb (https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/chapter04_getting-started-with-neural-networks.ipynb)

In [1]:

```python
import os
import sys
# //*** Imports and Load Data
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#//*** Use the whole window in the IPYNB editor
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>

#//*** Maximize columns and rows displayed by pandas
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', None)


from tensorflow import keras
```

In [2]:

```python
#//***********************************************************
#//*** Attempt to modularize a Sequential Keras Module.
#//***********************************************************
def build_model(**kwargs):
    #//*** Define the Model
    from tensorflow.keras import models
    from tensorflow.keras import layers
    from tensorflow.keras import optimizers


    #//*****************************
    #//*** Set Default values
    #//*****************************

    #//*** Total Layers is the total layers including the input l
    total_layers = 2

    #//*** Hidden units to be appled to all layers except the las
    hidden_units = 16
    #//*** Activation Function to be applied to all layers except
    first_activation = "relu"

```

```
    #//*** Activation Function for the last layer. No Activation
    final_activation=None

    #//*** Complie Optimzer
    optimizer='rmsprop'

    #//*** Loss Function for Optimizer
    loss = 'mse'

    #//*** Optimizer Metrics
    metrics=['accuracy']

    #//*** Tuple Defined Shape of the First Layer. None means thi
    shape = None

    #//*** Apply compiler to the model
    do_compile = True

    #//*** Number of Units (outputs) for the output layer.
    output_layer = 1

    #//*** Print a Representation of the Model
    display_model = True

    #//*** Modify the default settings with **kwargs
    #//*** Apply Kwargs
    for key,value in kwargs.items():

        if key == 'layers':
            total_layers=value

        if key == 'hidden_units':
            hidden_units=value

        if key == 'loss':
            loss=value

        if key == 'first_activation':
            first_activation=value

        if key == 'final_activation':
            final_activation=value

        if key == 'optimizer':
            optimizer=value

        if key == 'metrics':
            metrics=value

        if key == 'shape':
            shape = value

        if key == 'compile':
            do_compile = value

        if key == 'output_layer':
```

```
            output_layer = value

        if key == 'display_model':
            display_model = value

    disp = ""
    #//*** Initialize the model
    model = models.Sequential()

    if display_model:
        disp += "models.Sequential()"
        disp +="\n"

    #//*** Add the First Layer. Include an Input_Shape paramter i
    if shape == None:
        #//*** Add First Layer
        model.add(layers.Dense(hidden_units, activation=first_act
        if display_model:
            disp += f"model.add(layers.Dense({hidden_units}, acti
            disp +="\n"

    else:
        #//*** Add First Layer
        model.add(layers.Dense(hidden_units, activation=first_act

        if display_model:
            disp += f"model.add(layers.Dense({hidden_units}, acti
            disp +="\n"


    #//*** Add Additional Layers if total_layers greater than 2
    for x in range(total_layers-2):

        #//*** These are basic layers with same number of hidden
        model.add(layers.Dense(hidden_units, activation=first_act
        if display_model:
            disp += f"model.add(layers.Dense({hidden_units}, acti
            disp +="\n"



    #//*** Add Final Layer

    if final_activation == None:
        model.add(layers.Dense(output_layer))

        if display_model:
            disp += f"model.add(layers.Dense({output_layer}))"
            disp +="\n"

    else:
        model.add(layers.Dense(output_layer, activation=final_act

        if display_model:
            disp += f"model.add(layers.Dense({output_layer}, acti
            disp +="\n"
```

```
    #//*** Compile Model
    if do_compile:

        model.compile(optimizer=optimizer,loss=loss,metrics=metri

        if display_model:
            disp += f"model.compile(optimizer={optimizer},loss={l
            disp +="\n"

    if display_model:
        print(disp)

    return model

```

Predicting house prices: A regression example

In [3]:

```
#//*** Import the housing Dataset from Keras
from tensorflow.keras.datasets import boston_housing
```

Type *Markdown* and LaTeX: α^2

In [4]:

```
print("Train Shape: ", train_data.shape)
```

```
Train Shape:  (404, 13)
Test Shape:  (102, 13)
```

Need Notes on normalizing the Data

And each feature in the input data (for example, the crime rate) has a different scale. For instance, some values are proportions, which take values between 0 and 1; others take values between 1 and 12, oth-ers between 0 and 100, and so on.

As you can see, you have 404 training samples and 102 test samples, each with 13 numerical features, such as per capita crime rate, average number of rooms per dwelling, accessibility to highways, and so on. The targets are the median values of owner-occupied homes, in thousands of dollars:

Normalization

feature-wise normalization: Subtract the Feature (column) Mean and Divide by the Standard Deviation

It would be problematic to feed into a neural network values that all take wildly differ-ent ranges. The network might be able to automatically adapt to such heterogeneousdata, but it would definitely make learning more difficult. A widespread best practiceto deal with such data is to do feature-wise normalization: for each feature in the input data (a column in the input data matrix), you subtract the mean of the feature anddivide by the standard deviation, so that the feature is centered around 0 and has aunit standard deviation. This is easily done in Numpy.

Note: that the quantities used for normalizing the test data are computed using the training data.

You should never use in your workflow any quantity computed on the test data, even for something as simple as data normalization.

In [5]:

```
#//*******************************
#//*** Normalize the Data
#//*******************************

#//*** Get the Mean of each Column in the Matrix
mean = train_data.mean(axis=0)

#//*** Subtract the Mean
train_data -= mean

#//*** Get the Standard Deviation
std = train_data.std(axis=0)

#//*** Divide by the Standard Deviation
train_data /= std

#//*** Subtract the Mean from the test Data
test_data -= mean

#//*** Divide the Standard Deviation from the Test Data
```

Because so few samples are available, you'll use a very small network with two hidden layers, each with 64 units. In general, the less training data you have, the worse overfitting will be, and using a small network is one way to mitigate overfitting.

The network ends with a single unit and no activation (it will be a linear layer). This isa typical setup for scalar regression (a regression where you're trying to predict a singlecontinuous value). Applying an activation function would constrain the range the out-put can take; for instance, if you applied a sigmoid activation function to the last layer,the network could only learn to predict values between 0 and 1. Here, because the lastlayer is purely linear, the network is free to learn to predict values in any range.

Note: that you compile the network with the mse loss function—mean squared error,the square of the difference between the predictions and the targets. This is a widely used loss function for regression problems. You're also monitoring a new metric during training: mean absolute error (MAE). It's the absolute value of the difference between the predictions and the targets. For instance, an MAE of 0.5 on this problem would mean your predictions are off by $500 on average.

Validate the Model ysubf K-fold validation

To evaluate your network while you keep adjusting its parameters (such as the number of epochs used for training), you could split the data into a training set and a valida-tion set, as you did in the previous examples. But because you have so few data points, the validation set would end up being very small (for instance, about 100 examples). As a consequence, the validation scores might change a lot depending on which datapoints you chose to use for validation and which you chose for training: the validations cores might have a high variance with regard to the validation split. This would prevent you from reliably evaluating your model. The best practice in such situations is to use K-fold cross-validation.It consists of splitting the available data into K partitions (typically K = 4 or 5), instantiating K identical models, and training each one on K – 1 partitions while evaluating onthe remaining partition. The validation score for the model used is then the average ofthe K validation scores obtained. In terms of code, this is straightforward.

Instead of selecting a Validation Subset, K-Fold validation runs splits the data into multiple different validation sets and scores them all. The average of the validations is a validation estimate of the model.

In [6]:

```
#//**********************************
#//*** Book Supplied Model Settings
#//**********************************
layers = 3
hidden_units = 64
first_activation = "relu"
optimizer = "rmsprop"
loss = 'mse'
metrics = ['mae']


#//*** F-Fold Validation
k = 4
num_val_samples = len(train_data) // k #//*** Floor Division
num_epochs = 100
all_scores = []
for i in range(k):
    print(f"Processing fold #{i}")
    val_data = train_data[i * num_val_samples: (i + 1) * num_val_s
    val_targets = train_targets[i * num_val_samples: (i + 1) * num
    partial_train_data = np.concatenate(
        [train_data[:i * num_val_samples],
         train_data[(i + 1) * num_val_samples:]],
        axis=0)
    partial_train_targets = np.concatenate(
        [train_targets[:i * num_val_samples],
         train_targets[(i + 1) * num_val_samples:]],
        axis=0)

    model = build_model(
        layers=layers,
        hidden_units = hidden_units,
        first_activation = first_activation,
        optimizer=optimizer,
        loss=loss,
        metrics=metrics,
        output_layer = 1
    )

    model.fit(partial_train_data, partial_train_targets,
              epochs=num_epochs, batch_size=16, verbose=0)
    val_mse, val_mae = model.evaluate(val_data, val_targets, verbo
    all_scores.append(val_mae)

```

```
Processing fold #0
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #1
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #2
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #3
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
```

In [7]:

```python
print("All Scores: ", all_scores)
```

```
All Scores:  [1.8729946613311768, 2.6107888221740723, 2.4159820079803
467, 2.37795090675354]
Mean Scores:  2.319429099559784
```

In [8]:

```python
#//*** Saving the validation logs of each fold
num_epochs = 500
all_mae_histories = []
for i in range(k):
    print(f"Processing fold #{i}")
    val_data = train_data[i * num_val_samples: (i + 1) * num_val_s
    val_targets = train_targets[i * num_val_samples: (i + 1) * num
    partial_train_data = np.concatenate(
        [train_data[:i * num_val_samples],
         train_data[(i + 1) * num_val_samples:]],
        axis=0)
    partial_train_targets = np.concatenate(
        [train_targets[:i * num_val_samples],
         train_targets[(i + 1) * num_val_samples:]],
        axis=0)
    model = build_model(
        layers=layers,
        hidden_units = hidden_units,
        first_activation = first_activation,
        optimizer=optimizer,
        loss=loss,
        metrics=metrics,
```

```
        output_layer = 1
    )
    history = model.fit(partial_train_data, partial_train_targets,
                        validation_data=(val_data, val_targets),
                        epochs=num_epochs, batch_size=16, verbose=

    mae_history = history.history["val_mae"]
    all_mae_histories.append(mae_history)

```

```
Processing fold #0
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #1
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #2
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

Processing fold #3
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])
```

In [9]:

```
#//*** Building the history of successive mean K-fold validation S
average_mae_history = [
```

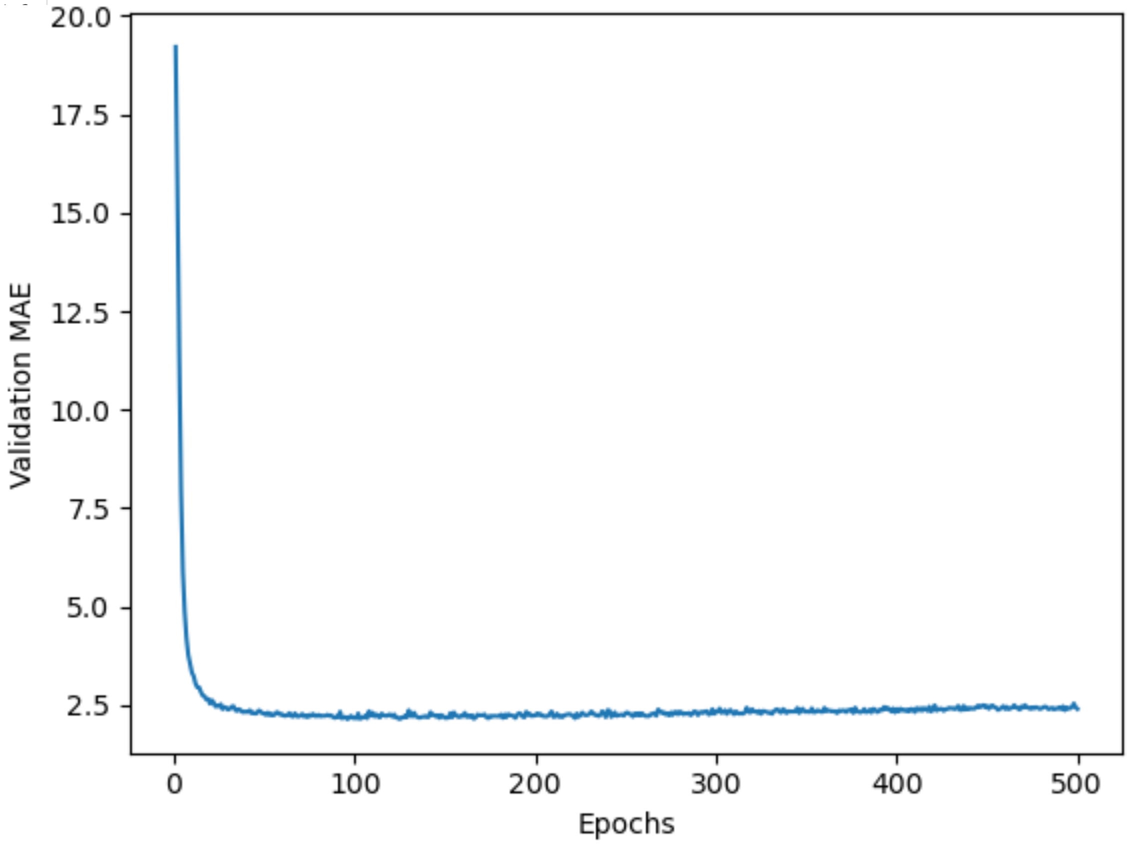
In [10]:

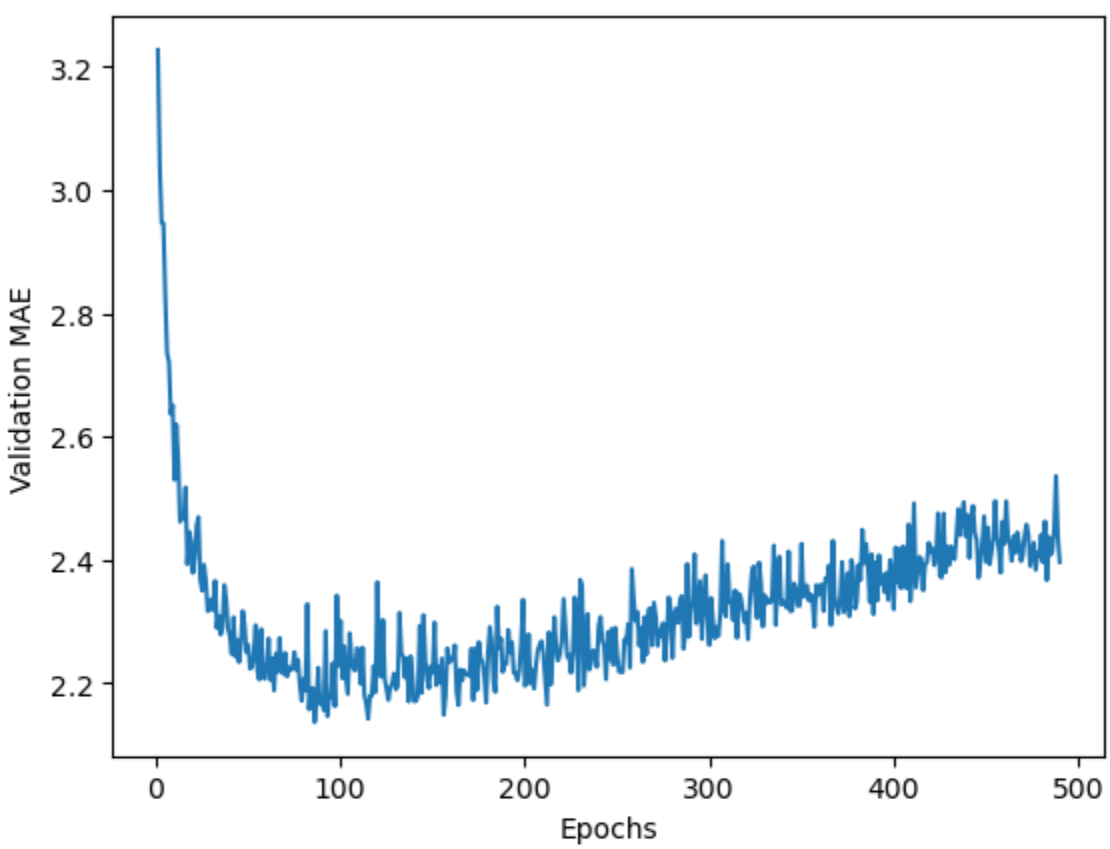
```
#//*** Plotting Validation scores
plt.plot(range(1, len(average_mae_history) + 1), average_mae_histo
plt.xlabel("Epochs")
plt.ylabel("Validation MAE")
plt.show()

#//*** Plotting Validation scores excluding the first 10 data Poir


truncated_mae_history = average_mae_history[10:]
plt.plot(range(1, len(truncated_mae_history) + 1), truncated_mae_h
plt.xlabel("Epochs")
plt.ylabel("Validation MAE")
plt.show()
```

15





In [11]:

```
#//*** Training the Final Model
#model = build_model()
```

```python


#//**************************
#//*** Book Supplied Settings
#//**************************
layers = 3
hidden_units = 64
first_activation = "relu"
optimizer = "rmsprop"
loss = 'mse'
metrics = ['mae']
model = build_model(
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    optimizer=optimizer,
    loss=loss,
    metrics=metrics,
    output_layer = 1
)

model.fit(train_data, train_targets,
          epochs=130, batch_size=16, verbose=0)
test_mse_score, test_mae_score = model.evaluate(test_data, test_ta

print("test_mae_score: ",test_mae_score)

#//*** Generate Predictions on the test_data
predictions = model.predict(test_data)
print("Predictions: ", predictions[0])

predictions = predictions.flatten()

```

```
models.Sequential()
model.add(layers.Dense(64, activation=relu ))
model.add(layers.Dense(64, activation=relu))
model.add(layers.Dense(1))
model.compile(optimizer=rmsprop,loss=mse,metrics=['mae'])

4/4 [==============================] - 0s 0s/step - loss: 16.9921 - m
ae: 2.5225
test_mae_score:  2.5225348472595215
Predictions:  [9.462795]
```

In [ ]:

In [15]:

```
#//*** Plot Predicted vs actual Values
plt.plot(range(1, len(predictions) + 1), test_targets, "bo", label
plt.plot(range(1, len(predictions) + 1), predictions, "b", label="
plt.ylabel("Prices")
plt.legend()
plt.title("Predicted vs Actual Housing Prices")
```