

# An Introduction to Deep Learning With Python

## [3.4] Predicting house prices: a regression example

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pgs: 85 - 91

### The Boston Housing Price dataset

```
In [1]: from keras.datasets import boston_housing
        (train_data, train_targets), (test_data, test_targets) = boston_housing.load_data()
```

Using TensorFlow backend.

Downloading data from [https://s3.amazonaws.com/keras-datasets/boston\\_housing.npz](https://s3.amazonaws.com/keras-datasets/boston_housing.npz)  
57344/57026 [=====] - 0s 5us/step

```
In [2]: train_data.shape
```

```
Out[2]: (404, 13)
```

```
In [3]: test_data.shape
```

```
Out[3]: (102, 13)
```

```
In [4]: train_targets[0:20]
```

```
Out[4]: array([15.2, 42.3, 50. , 21.1, 17.7, 18.5, 11.3, 15.6, 15.6, 14.4, 12.1,
               17.9, 23.1, 19.9, 15.7,  8.8, 50. , 22.5, 24.1, 27.5])
```

### Preparing the data

Normalizing the data

```
In [5]: mean = train_data.mean(axis=0)
        train_data -= mean
        std = train_data.std(axis=0)
        train_data /= std

        test_data -= mean
        test_data /= std
```

### Building your network

```
In [6]: from keras import models
        from keras import layers

        def build_model():
            model = models.Sequential()
            model.add(layers.Dense(64, activation='relu', input_shape=(train_data.shape[1],)))
            model.add(layers.Dense(64, activation='relu'))
            model.add(layers.Dense(1))
            model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])
            return model
```

## Validating your approach using K-fold validation

```
In [8]: import numpy as np

        k = 4
        num_val_samples = len(train_data) // k
        num_epochs = 100
        all_scores = []

        for i in range(k):
            print('processing fold #', i)
            val_data = train_data[i * num_val_samples:(i + 1) * num_val_samples]
            val_targets = train_targets[i * num_val_samples:(i + 1) * num_val_samples]

            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()
            model.fit(partial_train_data, partial_train_targets,
                      epochs=num_epochs, batch_size=1, verbose=0)
            val_mse, val_mae = model.evaluate(val_data, val_targets, verbose=0)
            all_scores.append(val_mae)

        processing fold # 0
        processing fold # 1
        processing fold # 2
        processing fold # 3
```

```
In [9]: all_scores
```

```
Out[9]: [2.1076202581424526, 2.2745308852431796, 3.033626646098524, 2.431880310030267]
```

```
In [10]: np.mean(all_scores)
```

```
Out[10]: 2.4619145248786056
```

## Saving the validation logs at each fold

```

In [11]: num_epochs = 500
all_mae_histories = []
for i in range(k):
    print('processing fold #', i)
    val_data = train_data[i * num_val_samples: (i + 1) * num_val_samples]
    val_targets = train_targets[i * num_val_samples: (i + 1) * num_val_samples]

    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()
    history = model.fit(partial_train_data, partial_train_targets,
                        validation_data=(val_data, val_targets),
                        epochs=num_epochs, batch_size=1, verbose=0)
    mae_history = history.history['val_mean_absolute_error']
    all_mae_histories.append(mae_history)

processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3

```

```

In [12]: average_mae_history = [np.mean([x[i] for x in all_mae_histories]) for i in range(num_
epochs)]

```

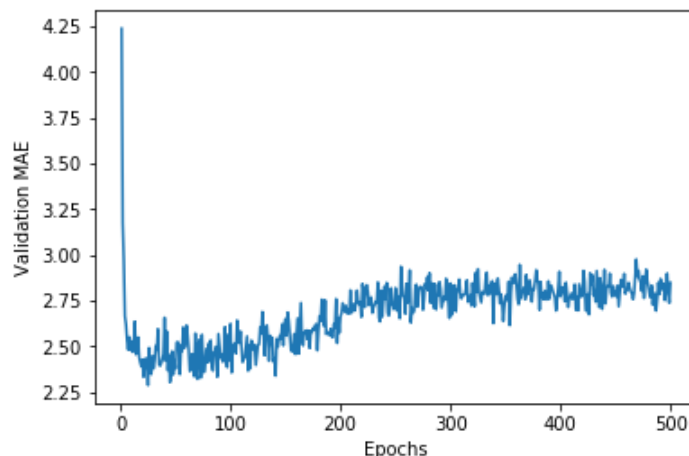
## Plotting validation scores

```

In [14]: import matplotlib.pyplot as plt

plt.plot(range(1, len(average_mae_history) + 1), average_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()

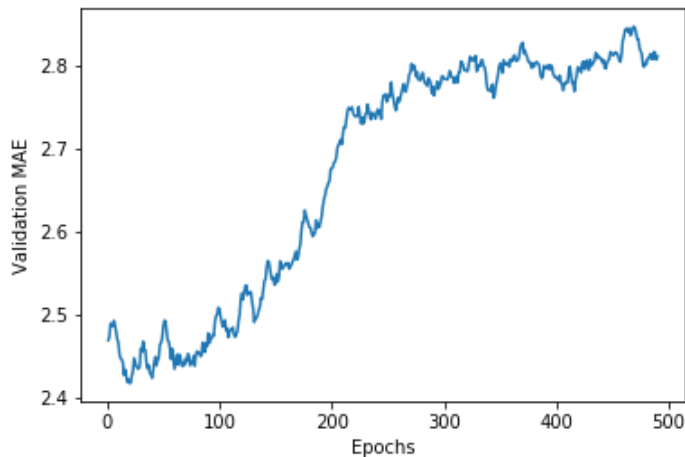
```



```
In [15]: def smooth_curve(points, factor=0.9):
smoothed_points = []
for point in points:
    if smoothed_points:
        previous = smoothed_points[-1]
        smoothed_points.append(previous * factor + point * (1 - factor))
    else:
        smoothed_points.append(point)
return smoothed_points

smooth_mae_history = smooth_curve(average_mae_history[10:])

plt.plot(range(1, len(smooth_mae_history) + 1), smooth_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



## Training the final model

```
In [16]: model = build_model()
model.fit(train_data, train_targets,
          epochs=80, batch_size=16, verbose=0)
test_mse_score, test_mae_score = model.evaluate(test_data, test_targets)
```

102/102 [=====] - 0s 1ms/step

```
In [17]: test_mae_score
```

```
Out[17]: 2.515716029148476
```

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