

# experiment\_6

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Course Name:	Deep Learning Lab
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**0.1 Load the Boston Housing dataset available in Keras. The dataset contains 13 numerical features about houses (crime rate, average rooms, property tax, etc.) and the target is the median house price in \$1000s**

```
[1]: from tensorflow import keras
      from keras.datasets import boston_housing

      (x_train,y_train),(x_test,y_test) = boston_housing.load_data()
```

Downloading data from [https://storage.googleapis.com/tensorflow/tf-keras-datasets/boston\\_housing.npz](https://storage.googleapis.com/tensorflow/tf-keras-datasets/boston_housing.npz)  
57026/57026 0s 3us/step

## 0.1.1 Scaling the data

```
[3]: from sklearn.preprocessing import StandardScaler
      scaler = StandardScaler()
      x_train_scaled = scaler.fit_transform(x_train)
      x_test_scaled = scaler.transform(x_test)
```

```
[4]: from keras.models import Sequential
      from keras.layers import Dense, Flatten, Dropout
      from keras.optimizers import SGD
      from keras.callbacks import EarlyStopping

      import warnings
      warnings.filterwarnings('ignore')
```

### 0.1.2 building the model

```
[29]: model = Sequential()
model.add(Flatten(input_shape = (13,)))
model.add(Dense(128, activation = 'relu'))
model.add(Dense(32, activation = 'relu'))
model.add(Dense(1, activation = 'linear'))

model.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
flatten_3 (Flatten)	(None, 13)	0
dense_9 (Dense)	(None, 128)	1,792
dense_10 (Dense)	(None, 32)	4,128
dense_11 (Dense)	(None, 1)	33

Total params: 5,953 (23.25 KB)

Trainable params: 5,953 (23.25 KB)

Non-trainable params: 0 (0.00 B)

```
[30]: sgd = SGD(learning_rate=0.001, momentum = 0.9 )
estop = EarlyStopping(monitor='val_loss', min_delta = 1e-5, mode = 'min',
    ↪patience = 5, verbose = 1, restore_best_weights=True)
model.compile(loss = 'mean_squared_error', optimizer = sgd, metrics = [keras.
    ↪metrics.R2Score()])
history = model.fit(x_train_scaled, y_train, batch_size = 32, epochs = 1000,
    ↪verbose = 1 , validation_split = 0.2, callbacks=estop)
```

Epoch 1/1000

11/11 1s 23ms/step -

loss: 525.1088 - r2\_score: -5.1942 - val\_loss: 152.1705 - val\_r2\_score: -0.8004

Epoch 2/1000

11/11 0s 7ms/step - loss:

206.3481 - r2\_score: -1.7244 - val\_loss: 232.1746 - val\_r2\_score: -1.7469

Epoch 3/1000

```

11/11          0s 9ms/step - loss:
127.4160 - r2_score: -0.4914 - val_loss: 46.9334 - val_r2_score: 0.4447
Epoch 4/1000
11/11          0s 9ms/step - loss:
63.1190 - r2_score: 0.1719 - val_loss: 138.8533 - val_r2_score: -0.6428
Epoch 5/1000
11/11          0s 9ms/step - loss:
85.9044 - r2_score: -0.0896 - val_loss: 42.2353 - val_r2_score: 0.5003
Epoch 6/1000
11/11          0s 9ms/step - loss:
51.4902 - r2_score: 0.3322 - val_loss: 17.8007 - val_r2_score: 0.7894
Epoch 7/1000
11/11          0s 7ms/step - loss:
22.0394 - r2_score: 0.7817 - val_loss: 13.2581 - val_r2_score: 0.8431
Epoch 8/1000
11/11          0s 7ms/step - loss:
11.5028 - r2_score: 0.8665 - val_loss: 12.2059 - val_r2_score: 0.8556
Epoch 9/1000
11/11          0s 7ms/step - loss:
10.9144 - r2_score: 0.8588 - val_loss: 12.3937 - val_r2_score: 0.8534
Epoch 10/1000
11/11          0s 7ms/step - loss:
11.1187 - r2_score: 0.8797 - val_loss: 11.3707 - val_r2_score: 0.8655
Epoch 11/1000
11/11          0s 7ms/step - loss:
11.3114 - r2_score: 0.8693 - val_loss: 11.1943 - val_r2_score: 0.8676
Epoch 12/1000
11/11          0s 7ms/step - loss:
10.8496 - r2_score: 0.8373 - val_loss: 12.1394 - val_r2_score: 0.8564
Epoch 13/1000
11/11          0s 7ms/step - loss:
7.9768 - r2_score: 0.9096 - val_loss: 12.3955 - val_r2_score: 0.8533
Epoch 14/1000
11/11          0s 7ms/step - loss:
8.1842 - r2_score: 0.8934 - val_loss: 12.1603 - val_r2_score: 0.8561
Epoch 15/1000
11/11          0s 7ms/step - loss:
7.9954 - r2_score: 0.9130 - val_loss: 12.0649 - val_r2_score: 0.8573
Epoch 16/1000
11/11          0s 8ms/step - loss:
11.3025 - r2_score: 0.8788 - val_loss: 13.3281 - val_r2_score: 0.8423
Epoch 16: early stopping
Restoring model weights from the end of the best epoch: 11.

```

```

[31]: score = model.evaluate(x_test_scaled, y_test, verbose = 1)
      print("Test loss:", score[0])
      print("R2 score:", score[1])

```

4/4                      0s 7ms/step - loss:  
20.3991 - r2\_score: 0.7324  
Test loss: 26.721763610839844  
R2 score: 0.6789939403533936

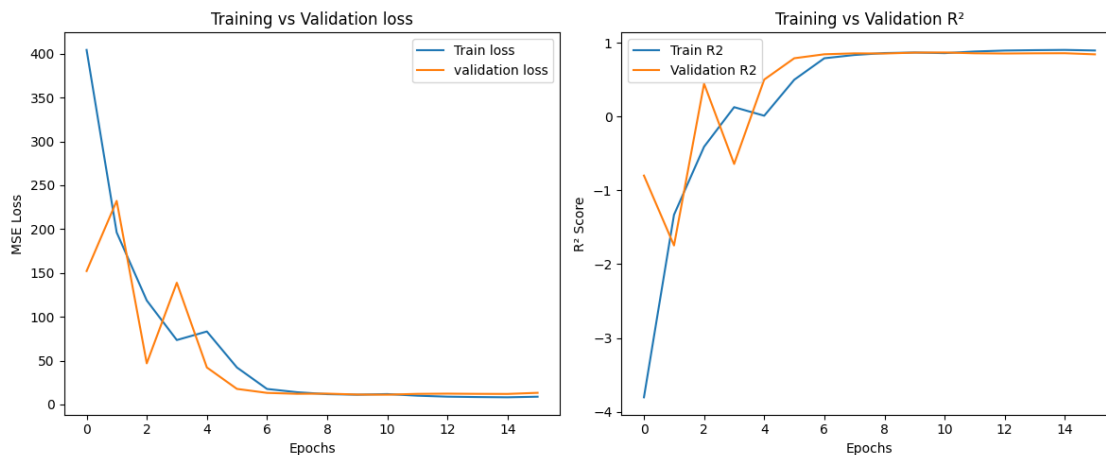
### 0.1.3 plotting the graph

```
[32]: import matplotlib.pyplot as plt

plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
plt.plot(history.history['loss'], label = 'Train loss')
plt.plot(history.history['val_loss'], label = 'validation loss')
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.title("Training vs Validation loss")
plt.legend()

plt.subplot(1,2,2)
plt.plot(history.history['r2_score'], label='Train R2')
plt.plot(history.history['val_r2_score'], label='Validation R2')
plt.xlabel('Epochs')
plt.ylabel('R2 Score')
plt.title('Training vs Validation R2')
plt.legend()

plt.tight_layout()
plt.show()
```



## 0.2 Question 2: Hyperparameter Tuning

### 0.2.1 Perform hyperparameter tuning for the following hyperparameters:

- Number of neurons in each hidden layer.
- activation function in each hidden layer.
- Learning rate of the optimizer.
- Momentum parameter in SGD

Report the best set of hyperparameters that improves performance.

```
[41]: import keras_tuner as kt

def build_model(hp):
    model = Sequential()
    activation = hp.Choice('activation', values = ['relu','sigmoid','tanh'])
    ## input layer
    model.add(Flatten(input_shape = (13,)))
    ## Tuning the number of neurons in the hidden layer
    units_1 = hp.Int('units_1', min_value = 32, max_value = 512, step = 32)
    model.add(Dense(units_1, activation = activation))
    units_2 = hp.Int('units_2', min_value = 32, max_value = 512, step = 32)
    model.add(Dense(units_2, activation = activation))

    ## Output layer for regression
    model.add(Dense(1, activation = 'linear'))

    ## tuning optimizer hyperparameters
    learning_rate = hp.Choice('learning_rate', values = [0.001,0.01,0.005,0.05])
    momentum = hp.Choice('momentum', values = [0.0,0.5,0.8,0.9])

    optimizer = SGD(learning_rate=learning_rate, momentum = momentum)

    ## compiling the model
    model.compile(optimizer = optimizer,
                  loss = 'mse',
                  metrics = [keras.metrics.R2Score(name = 'r2_score')])
    return model

## Defining the tuner
tuner = kt.RandomSearch(
    build_model,
    objective = kt.Objective('val_r2_score', direction = 'max'),
    max_trials = 10,
    executions_per_trial = 1,
    overwrite = True,
    directory = 'tuner_results',
    project_name = 'boston_housing'
)
```

```

estop = EarlyStopping(monitor = 'val_loss', patience = 5, min_delta = 1e-5,
↳restore_best_weights=True)

tuner.search(
    x_train_scaled, y_train,
    epochs = 100,
    validation_split = 0.2,
    batch_size = 32,
    callbacks = [estop]
)

## Evaluating the best model
best_model = tuner.get_best_models(num_models = 1)[0]
test_loss, test_r2 = best_model.evaluate(x_test_scaled, y_test, verbose=1)

print("Best Hyperparameters:", tuner.get_best_hyperparameters()[0].values)
print("Test Loss:", test_loss)
print("Test R2:", test_r2)

```

Trial 10 Complete [00h 00m 03s]  
val\_r2\_score: 0.6699258089065552

Best val\_r2\_score So Far: 0.8757489323616028  
Total elapsed time: 00h 00m 49s  
4/4                    0s 10ms/step - loss:  
21.6815 - r2\_score: 0.7175  
Best Hyperparameters: {'activation': 'sigmoid', 'units\_1': 64, 'units\_2': 192,  
'learning\_rate': 0.005, 'momentum': 0.8}  
Test Loss: 26.86515998840332  
Test R2: 0.6772713661193848

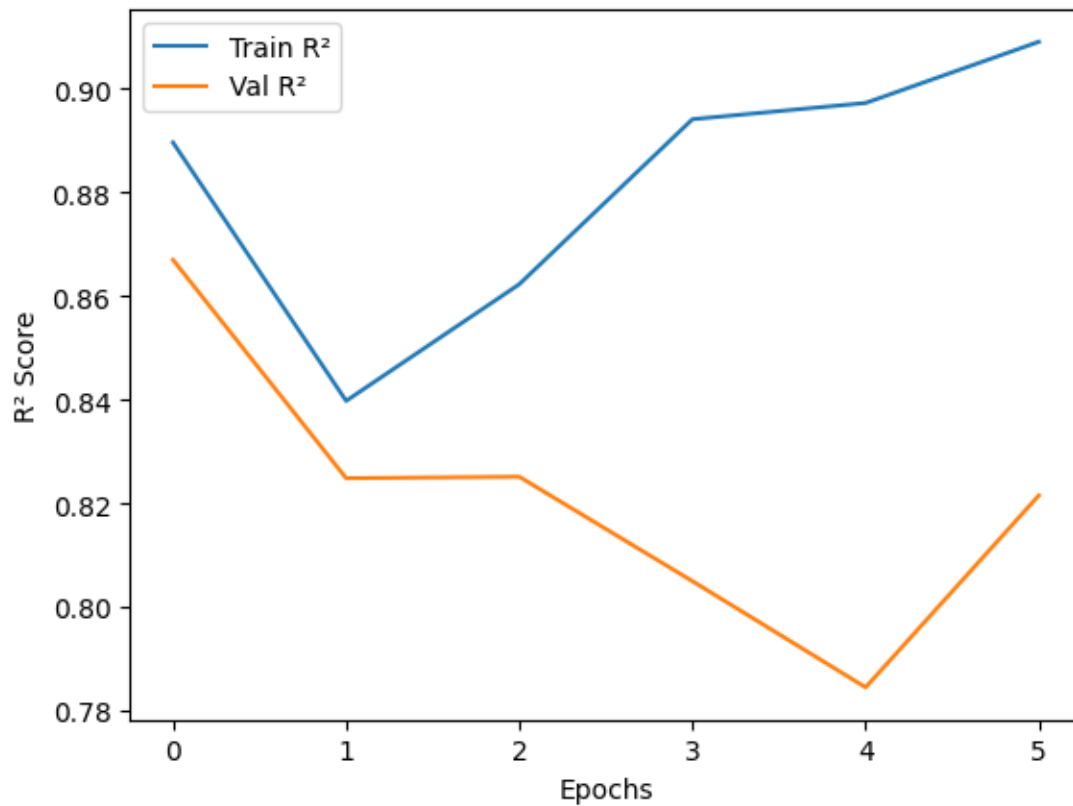
```

[42]: history = model.fit(x_train_scaled, y_train, batch_size = 32, epochs = 1000,
↳verbose = 1, validation_split = 0.2, callbacks=estop)
plt.plot(history.history['r2_score'], label='Train R2')
plt.plot(history.history['val_r2_score'], label='Val R2')
plt.xlabel('Epochs')
plt.ylabel('R2 Score')
plt.legend()
plt.show()

```

Epoch 1/1000  
11/11                    0s 22ms/step -  
loss: 8.3707 - r2\_score: 0.8878 - val\_loss: 11.2401 - val\_r2\_score: 0.8670  
Epoch 2/1000  
11/11                    0s 11ms/step -  
loss: 11.2104 - r2\_score: 0.8672 - val\_loss: 14.8029 - val\_r2\_score: 0.8249  
Epoch 3/1000

```
11/11          0s 10ms/step -  
loss: 12.0472 - r2_score: 0.8657 - val_loss: 14.7791 - val_r2_score: 0.8251  
Epoch 4/1000  
11/11          0s 11ms/step -  
loss: 10.3816 - r2_score: 0.8585 - val_loss: 16.4824 - val_r2_score: 0.8050  
Epoch 5/1000  
11/11          0s 13ms/step -  
loss: 8.5413 - r2_score: 0.8910 - val_loss: 18.2147 - val_r2_score: 0.7845  
Epoch 6/1000  
11/11          0s 11ms/step -  
loss: 8.2253 - r2_score: 0.9061 - val_loss: 15.0843 - val_r2_score: 0.8215
```



### 0.3 Question 3: Optimizer Comparison

- Try at least three optimizers (e.g., SGD with momentum, RMSprop, Adam).
- Train the same model architecture with each optimizer.
- Compare their performances (using test MSE).
- Report which optimizer gives the best results.

Using the optimal architecture from the prev tuning, here we tune the optimizer

```

[46]: from keras.optimizers import SGD, RMSprop, Adam

def build_model(hp):
    model = Sequential()

    # using the best parameters from the prev tuning
    model.add(Dense(64, activation='sigmoid', input_shape=(x_train_scaled.
↪shape[1],)))
    model.add(Dense(192, activation='sigmoid'))
    model.add(Dense(1)) # output layer

    # Optimizer choice
    optimizer_choice = hp.Choice('optimizer', ['SGD', 'RMSprop', 'Adam'])

    if optimizer_choice == 'SGD':
        optimizer = SGD(
            learning_rate=hp.Choice('lr_sgd', [1e-2, 1e-3, 1e-4]),
            momentum=hp.Choice('momentum', [0.0, 0.8, 0.9])
        )
    elif optimizer_choice == 'RMSprop':
        optimizer = RMSprop(
            learning_rate=hp.Choice('lr_rms', [1e-2, 1e-3, 1e-4])
        )
    else:
        optimizer = Adam(
            learning_rate=hp.Choice('lr_adam', [1e-2, 1e-3, 1e-4])
        )

    model.compile(optimizer=optimizer, loss='mse', metrics=['mse'])

    return model

tuner = kt.RandomSearch(
    build_model,
    objective='val_mse',
    max_trials=10,
    executions_per_trial=1,
    overwrite=True,
    directory='optimizer_tuning',
    project_name='boston_housing_opt'
)

# Early stopping to avoid overfitting
estop = EarlyStopping(monitor='val_loss', min_delta = 1e-5, patience=5,
↪restore_best_weights=True)

tuner.search(

```



```

    x_train_scaled, y_train,
    epochs=200,
    validation_split=0.2,
    batch_size=32,
    callbacks=[estop],
    verbose=1
)

best_model = tuner.get_best_models(num_models=1)[0]
best_hp = tuner.get_best_hyperparameters(1)[0]

print("Best Optimizer Hyperparameters:", best_hp.values)

history = best_model.fit(
    x_train_scaled, y_train,
    validation_split=0.2,
    epochs=200,
    batch_size=32,
    callbacks=[estop],
    verbose=1
)

test_loss, test_mse = best_model.evaluate(x_test_scaled, y_test, verbose=1)
print(f"Test MSE: {test_mse:.4f}")

from sklearn.metrics import r2_score
y_pred = best_model.predict(x_test_scaled)
test_r2 = r2_score(y_test, y_pred)
print(f"Test R2: {test_r2:.4f}")

```

Trial 10 Complete [00h 00m 30s]

val\_mse: 15.189946174621582

Best val\_mse So Far: 9.348682403564453

Total elapsed time: 00h 02m 28s

Best Optimizer Hyperparameters: {'optimizer': 'Adam', 'lr\_sgd': 0.001, 'momentum': 0.0, 'lr\_adam': 0.01}

Epoch 1/200

11/11 1s 17ms/step -

loss: 9.8192 - mse: 9.8192 - val\_loss: 14.4357 - val\_mse: 14.4357

Epoch 2/200

11/11 0s 7ms/step - loss:

8.9413 - mse: 8.9413 - val\_loss: 10.3510 - val\_mse: 10.3510

Epoch 3/200

11/11 0s 7ms/step - loss:

9.0794 - mse: 9.0794 - val\_loss: 10.2321 - val\_mse: 10.2321

Epoch 4/200

```

11/11          0s 7ms/step - loss:
8.8217 - mse: 8.8217 - val_loss: 10.0367 - val_mse: 10.0367
Epoch 5/200
11/11          0s 8ms/step - loss:
11.4740 - mse: 11.4740 - val_loss: 14.4999 - val_mse: 14.4999
Epoch 6/200
11/11          0s 8ms/step - loss:
8.8971 - mse: 8.8971 - val_loss: 15.1635 - val_mse: 15.1635
Epoch 7/200
11/11          0s 7ms/step - loss:
12.8703 - mse: 12.8703 - val_loss: 18.7889 - val_mse: 18.7889
Epoch 8/200
11/11          0s 9ms/step - loss:
13.9182 - mse: 13.9182 - val_loss: 13.9935 - val_mse: 13.9935
Epoch 9/200
11/11          0s 8ms/step - loss:
9.4071 - mse: 9.4071 - val_loss: 10.5341 - val_mse: 10.5341
4/4           0s 6ms/step - loss:
17.4423 - mse: 17.4423
Test MSE: 22.8578
4/4           0s 14ms/step
Test R2: 0.7254

```

- Best Optimizer Hyperparameters: {'optimizer': 'Adam', 'lr\_sgd': 0.001, 'momentum': 0.0, 'lr\_adam': 0.01}