

# tuning

March 10, 2022

```
[1]: import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras import models, layers
from tensorflow import keras
from tensorflow.keras.callbacks import EarlyStopping
from data_generation import DenseGenerator, ChessPositionGen
import keras_tuner as kt

import datetime
%load_ext tensorboard
```

We'll start with the same setup as in `full-puzzle-model.ipynb`

```
[2]: # Setting paramaters on early stopping
earlystop = EarlyStopping(monitor='val_loss',
                           min_delta=0,
                           patience=5,
                           verbose=1,
                           mode='min',
                           restore_best_weights=True)

log_dir = "logs/fit/tuned" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
↳ histogram_freq=1)
```

```
[3]: # Memory management, likely not necessary, but used as a safety as per the
↳ documentation recommendations on using GPUS

gpus = tf.config.list_physical_devices('GPU')
if gpus:
    try:
        # Currently, memory growth needs to be the same across GPUs
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        logical_gpus = tf.config.list_logical_devices('GPU')
        print(len(gpus), "Physical GPUs,", len(logical_gpus), "Logical GPUs")
    except RuntimeError as e:
```

```
# Memory growth must be set before GPUs have been initialized
print(e)
```

1 Physical GPUs, 1 Logical GPUs

```
[4]: train = pd.read_csv('fens/train.csv')
     val = pd.read_csv('fens/val.csv')
```

```
[5]: train_dense_gen = DenseGenerator(train, batch_size=1024)
     val_dense_gen = DenseGenerator(val, batch_size=1024)
```

```
[5]: train_tune_gen = ChessPositionGen(train, batch_size=512)
     val_tune_gen = ChessPositionGen(val, batch_size=512)
```

## 0.1 Multi Layer Perceptron model for comparison with the CNN versions

This model uses basic densely connected layers and uses a slight variation of the previously used data generator with no reshaping of the array.

```
[6]: dense_model = models.Sequential()
     dense_model.add(layers.Dense(832, input_shape=(832,), activation='relu'))
     dense_model.add(layers.Dense(64, activation='relu'))
     dense_model.add(layers.Dense(64, activation='relu'))
     dense_model.add(layers.Dense(1, activation='sigmoid'))
     dense_model.compile(optimizer="adam", loss="binary_crossentropy",
     ↪metrics=['acc'])
     dense_model.summary()

# Fitting the model
dense_history = dense_model.fit(x=train_dense_gen,
                               validation_data=val_dense_gen,
                               # steps_per_epoch=100,
                               epochs=15,
                               callbacks=[earlystop, tensorboard_callback]
                               )
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 832)	693056
dense_1 (Dense)	(None, 64)	53312
dense_2 (Dense)	(None, 64)	4160
dense_3 (Dense)	(None, 1)	65

Total params: 750,593  
Trainable params: 750,593  
Non-trainable params: 0

```
-----  
Epoch 1/15  
1977/1977 [=====] - 2590s 1s/step - loss: 0.4226 - acc:  
0.8320 - val_loss: 0.3911 - val_acc: 0.8487  
Epoch 2/15  
1977/1977 [=====] - 2598s 1s/step - loss: 0.3766 - acc:  
0.8544 - val_loss: 0.3697 - val_acc: 0.8579  
Epoch 3/15  
1977/1977 [=====] - 2574s 1s/step - loss: 0.3586 - acc:  
0.8620 - val_loss: 0.3572 - val_acc: 0.8626  
Epoch 4/15  
1977/1977 [=====] - 2570s 1s/step - loss: 0.3450 - acc:  
0.8670 - val_loss: 0.3475 - val_acc: 0.8660  
Epoch 5/15  
1977/1977 [=====] - 2565s 1s/step - loss: 0.3335 - acc:  
0.8710 - val_loss: 0.3412 - val_acc: 0.8686  
Epoch 6/15  
1977/1977 [=====] - 2572s 1s/step - loss: 0.3249 - acc:  
0.8740 - val_loss: 0.3370 - val_acc: 0.8703  
Epoch 7/15  
1977/1977 [=====] - 2562s 1s/step - loss: 0.3183 - acc:  
0.8763 - val_loss: 0.3307 - val_acc: 0.8719  
Epoch 8/15  
1977/1977 [=====] - 2564s 1s/step - loss: 0.3129 - acc:  
0.8783 - val_loss: 0.3280 - val_acc: 0.8732  
Epoch 9/15  
1977/1977 [=====] - 2562s 1s/step - loss: 0.3083 - acc:  
0.8798 - val_loss: 0.3256 - val_acc: 0.8743  
Epoch 10/15  
1977/1977 [=====] - 2569s 1s/step - loss: 0.3043 - acc:  
0.8814 - val_loss: 0.3233 - val_acc: 0.8749  
Epoch 11/15  
1977/1977 [=====] - 2570s 1s/step - loss: 0.3007 - acc:  
0.8826 - val_loss: 0.3214 - val_acc: 0.8754  
Epoch 12/15  
1977/1977 [=====] - 2571s 1s/step - loss: 0.2975 - acc:  
0.8838 - val_loss: 0.3194 - val_acc: 0.8766  
Epoch 13/15  
1977/1977 [=====] - 2570s 1s/step - loss: 0.2948 - acc:  
0.8848 - val_loss: 0.3193 - val_acc: 0.8766  
Epoch 14/15  
1977/1977 [=====] - 2570s 1s/step - loss: 0.2919 - acc:  
0.8857 - val_loss: 0.3180 - val_acc: 0.8761  
Epoch 15/15  
1977/1977 [=====] - 2568s 1s/step - loss: 0.2897 - acc:
```

0.8864 - val\_loss: 0.3165 - val\_acc: 0.8773

```
[9]: # dense_model.save('MLPmodel-Long-PB')
```

INFO:tensorflow:Assets written to: DenseModel-PB/assets

Initially this model was only trained for 15 epochs, then when it appeared that it might be roughly comparable with the CNN model, it was trained for another 15 (early stopped after 11, 26 epochs in total) for a more direct comparison.

```
[10]: dense_history = dense_model.fit(x=train_dense_gen,
                                     validation_data=val_dense_gen,
                                     epochs=15,
                                     callbacks=[earlystop, tensorboard_callback])
```

Epoch 1/15

1977/1977 [=====] - 2595s 1s/step - loss: 0.2872 - acc: 0.8874 - val\_loss: 0.3181 - val\_acc: 0.8767

Epoch 2/15

1977/1977 [=====] - 2590s 1s/step - loss: 0.2852 - acc: 0.8881 - val\_loss: 0.3158 - val\_acc: 0.8776ETA: 2:49 - 1 - ETA: 22s

Epoch 3/15

1977/1977 [=====] - 2582s 1s/step - loss: 0.2833 - acc: 0.8888 - val\_loss: 0.3150 - val\_acc: 0.8778

Epoch 4/15

1977/1977 [=====] - 2581s 1s/step - loss: 0.2816 - acc: 0.8895 - val\_loss: 0.3151 - val\_acc: 0.8781

Epoch 5/15

1977/1977 [=====] - 2569s 1s/step - loss: 0.2800 - acc: 0.8899 - val\_loss: 0.3153 - val\_acc: 0.8774

Epoch 6/15

1977/1977 [=====] - 2583s 1s/step - loss: 0.2784 - acc: 0.8904 - val\_loss: 0.3144 - val\_acc: 0.8785

Epoch 7/15

1977/1977 [=====] - 2601s 1s/step - loss: 0.2770 - acc: 0.8909 - val\_loss: 0.3159 - val\_acc: 0.8780

Epoch 8/15

1977/1977 [=====] - 2595s 1s/step - loss: 0.2756 - acc: 0.8914 - val\_loss: 0.3156 - val\_acc: 0.8782

Epoch 9/15

1977/1977 [=====] - 2589s 1s/step - loss: 0.2743 - acc: 0.8919 - val\_loss: 0.3155 - val\_acc: 0.8783

Epoch 10/15

1977/1977 [=====] - 2587s 1s/step - loss: 0.2731 - acc: 0.8923 - val\_loss: 0.3175 - val\_acc: 0.8785

Epoch 11/15

1977/1977 [=====] - 2588s 1s/step - loss: 0.2721 - acc: 0.8926 - val\_loss: 0.3160 - val\_acc: 0.8781

Restoring model weights from the end of the best epoch.  
Epoch 00011: early stopping

```
[12]: # dense_model.save('MLPmodel-Long.h5')
```

## 0.2 Autotuning

For further information on the Keras autotuner, consult the documentation.

```
[6]: def model_builder(hp):  
    """  
    Autotuner modeling function, based off the CNN model from the_  
    ↪full-puzzle-model notebook.  
    """  
    model = models.Sequential()  
  
    # Set Convolutional layer parameters  
    hp_filters = hp.Int('filters', min_value=16, max_value=128, step=8)  
    hp_ksize = hp.Int('kernel_size', min_value=2, max_value=8, step=2)  
  
    model.add(layers.Conv2D(filters=hp_filters, kernel_size=hp_ksize,_  
    ↪padding='same', input_shape=(8,8,13), activation='relu'))  
    model.add(layers.MaxPooling2D(2))  
    model.add(layers.Conv2D(filters=hp_filters, kernel_size=hp_ksize,_  
    ↪padding='same', activation='relu'))  
    model.add(layers.Flatten())  
  
    # Add dense tuning parameters  
    hp_units = hp.Int('units', min_value=16, max_value=128, step=8)  
    model.add(layers.Dense(units=hp_units, activation='relu'))  
    model.add(layers.Dense(1, activation='sigmoid'))  
    model.compile(optimizer="adam", loss="binary_crossentropy", metrics=['acc'])  
  
    return model  
  
tuner = kt.Hyperband(model_builder, objective='val_acc', max_epochs=10,_  
    ↪directory='tuner', project_name='CNN_tuning')
```

With the model\_builder function and tuner created, let's start the search. The steps per epoch have been reduced in order to finish searching in a reasonable amount of time.

```
[7]: tuner.search(x=train_tune_gen, validation_data=val_tune_gen,_  
    ↪steps_per_epoch=1000, callbacks=[earlystop])  
  
best_hps=tuner.get_best_hyperparameters()[0]  
print(best_hps)
```

Trial 30 Complete [02h 09m 36s]

val\_acc: 0.8775654435157776

Best val\_acc So Far: 0.8832182884216309

Total elapsed time: 02h 04m 53s

INFO:tensorflow:Oracle triggered exit

<keras\_tuner.engine.hyperparameters.HyperParameters object at 0x7f4850260a90>

With parameters found, we can now train our best model.

```
[16]: tuned_model = tuner.get_best_models(num_models=1)[0]
      tuned_model.build()
      tuned_model.summary()

      tuned_history = tuned_model.fit(x=train_tune_gen,
                                     validation_data=val_tune_gen,
                                     epochs=30,
                                     callbacks=[earlystop, tensorboard_callback])
```

WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.iter

WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta\_1

WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta\_2

WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.decay

WARNING:tensorflow:Unresolved object in checkpoint:

(root).optimizer.learning\_rate

WARNING:tensorflow:A checkpoint was restored (e.g. tf.train.Checkpoint.restore or tf.keras.Model.load\_weights) but not all checkpointed values were used. See above for specific issues. Use expect\_partial() on the load status object, e.g. tf.train.Checkpoint.restore(...).expect\_partial(), to silence these warnings, or use assert\_consumed() to make the check explicit. See

[https://www.tensorflow.org/guide/checkpoint#loading\\_mechanics](https://www.tensorflow.org/guide/checkpoint#loading_mechanics) for details.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 8, 8, 120)	99960
max_pooling2d (MaxPooling2D)	(None, 4, 4, 120)	0
conv2d_1 (Conv2D)	(None, 4, 4, 120)	921720
flatten (Flatten)	(None, 1920)	0
dense (Dense)	(None, 96)	184416
dense_1 (Dense)	(None, 1)	97

Total params: 1,206,193

Trainable params: 1,206,193

Non-trainable params: 0

```
-----  
Epoch 1/30  
3953/3953 [=====] - 2677s 677ms/step - loss: 0.2935 -  
acc: 0.8893 - val_loss: 0.2870 - val_acc: 0.8919  
Epoch 2/30  
3953/3953 [=====] - 2696s 682ms/step - loss: 0.2733 -  
acc: 0.8959 - val_loss: 0.2728 - val_acc: 0.8965  
Epoch 3/30  
3953/3953 [=====] - 2697s 682ms/step - loss: 0.2610 -  
acc: 0.9002 - val_loss: 0.2653 - val_acc: 0.8992  
Epoch 4/30  
3953/3953 [=====] - 2693s 681ms/step - loss: 0.2524 -  
acc: 0.9032 - val_loss: 0.2617 - val_acc: 0.9006  
Epoch 5/30  
3953/3953 [=====] - 2691s 681ms/step - loss: 0.2457 -  
acc: 0.9055 - val_loss: 0.2578 - val_acc: 0.9014  
Epoch 6/30  
3953/3953 [=====] - 2684s 679ms/step - loss: 0.2399 -  
acc: 0.9074 - val_loss: 0.2564 - val_acc: 0.9021  
Epoch 7/30  
3953/3953 [=====] - 2691s 681ms/step - loss: 0.2353 -  
acc: 0.9091 - val_loss: 0.2547 - val_acc: 0.9031  
Epoch 8/30  
3953/3953 [=====] - 2691s 681ms/step - loss: 0.2310 -  
acc: 0.9106 - val_loss: 0.2568 - val_acc: 0.9032  
Epoch 9/30  
3953/3953 [=====] - 2688s 680ms/step - loss: 0.2268 -  
acc: 0.9120 - val_loss: 0.2552 - val_acc: 0.9033  
Epoch 10/30  
3953/3953 [=====] - 2685s 679ms/step - loss: 0.2233 -  
acc: 0.9131 - val_loss: 0.2560 - val_acc: 0.9034  
Epoch 11/30  
3953/3953 [=====] - 2686s 680ms/step - loss: 0.2201 -  
acc: 0.9142 - val_loss: 0.2550 - val_acc: 0.9034  
Epoch 12/30  
3953/3953 [=====] - 2668s 675ms/step - loss: 0.2174 -  
acc: 0.9151 - val_loss: 0.2561 - val_acc: 0.9033  
Restoring model weights from the end of the best epoch.  
Epoch 00012: early stopping
```

```
[18]: # tuned_model.save("tuned_model-PB")
```

INFO:tensorflow:Assets written to: tuned\_model-PB/assets