model_pitching

April 30, 2020

```
[1]:
     import tensorflow as tf
     import pandas as pd
     import numpy as np
[2]: df = pd.read_csv('../core/output/pitchers.csv')
     indexer = df.reset_index()[['index', 'retroID']].to_dict()['retroID']
     y = df['Pitching'].values
[3]:
    df
                                     SHO
[3]:
             retroID
                         BAOpp
                                CG
                                           IPouts
                                                       Η
                                                            ER
                                                                 HR
                                                                       BB
                                                                             SO
     0
            aardd001
                       0.2574
                                  0
                                       0
                                             1011
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                                                                      183
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     1
            aased001
                       0.2508
                                22
                                             3328
                                                    1085
                                                           468
                                                                 89
                                                                      457
                                                                            641
     2
            abadf001
                       0.2447
                                  0
                                       0
                                              992
                                                     309
                                                           135
                                                                 42
                                                                      116
                                                                            280
     3
                       0.2786
                                37
                                       5
                                                    1405
                                                           627
                                                                      352
            abbog001
                                             3858
                                                                162
                                                                            484
     4
            abboj001
                       0.2804
                                31
                                       6
                                             5022
                                                    1779
                                                           791
                                                                154
                                                                      620
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     8020
                       0.2700
            zolds101
                                30
                                       5
                                             2788
                                                     956
                                                                 54
                                                                      301
                                                                            207
                                                           366
     8021
            zubeb101
                       0.2717
                                23
                                       3
                                             2358
                                                           374
                                                                 35
                                                                      468
                                                     767
                                                                            383
     8022
                       0.2286
            zumaj001
                                       0
                                              629
                                                     169
                                                            71
                                                                 18
                                                                      114
                                                                            210
     8023
            zuveg101
                       0.2760
                                  9
                                       2
                                             1927
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                                                           253
                                                                 56
                                                                      203
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     8024
            zycht001
                       0.2183
                                  0
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                                              218
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                   ΙP
                        K/9
                              BB/9
                                     HR/9
                                            BABIP
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                                                                               Pitching
     0
                                     1.09
                                            0.285
                                                    74.5
                                                           4.27
                                                                 4.45
            0.062360
                       9.08
                              4.89
                                                                         1.1
                                                                               0.602913
     1
                       5.20
                                     0.72
                                            0.282
            0.205233
                              3.71
                                                    73.4
                                                           3.80
                                                                 3.85
                                                                        11.7
                                                                               0.636924
     2
            0.061102
                              3.16
                                            0.281
                                                                 4.24
                       7.62
                                     1.14
                                                    77.7
                                                           3.67
                                                                         0.6
                                                                               0.603736
     3
                                            0.278
            0.237967
                       3.39
                              2.46
                                     1.13
                                                    69.3
                                                           4.39
                                                                 4.46
                                                                        10.2
                                                                               0.628847
     4
            0.309765
                       4.77
                              3.33
                                     0.83
                                            0.295
                                                    70.0
                                                           4.25
                                                                 4.25
                                                                        22.7
                                                                               0.666725
                                                                   . . .
     8020
            0.171925
                       2.00
                              2.91
                                     0.52
                                            0.267
                                                    70.7
                                                           3.54
                                                                 3.80
                                                                         9.3
                                                                               0.630540
     8021
            0.145445
                       4.39
                              5.36
                                     0.40
                                            0.283
                                                    69.0
                                                           4.28
                                                                 3.96
                                                                         3.3
                                                                               0.610437
     8022
            0.038711
                       9.01
                              4.89
                                     0.77
                                            0.267
                                                    78.7
                                                           3.00
                                                                 3.94
                                                                         2.7
                                                                               0.612847
     8023
            0.118817
                       3.12
                              2.84
                                            0.270
                                                    73.2
                                                           3.54
                                                                 3.93
                                     0.78
                                                                         1.9
                                                                               0.608497
     8024
            0.013360
                       9.91
                              4.21
                                     0.37
                                            0.293
                                                    79.1
                                                          2.72
                                                                 3.22
                                                                               0.611166
```

[8025 rows x 31 columns]

Building the Model

```
[4]: from sklearn.model_selection import train_test_split
[5]: X = df.drop(columns=['Pitching']).values
      y = df[['retroID', 'Pitching']].values
     When we do our train-test split, since it's random in how it splits up the data, we need to keep
     track of the appropriate keys (retro IDs) for each data point.
 [6]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,__
       →random_state=101)
      X_train_keys = np.asarray([x[0] for x in X_train])
      X_train = np.asarray([x[1:] for x in X_train])
      X_test_keys = np.asarray([x[0] for x in X_test])
      X_test = np.asarray([x[1:] for x in X_test])
      y_train_keys = np.asarray([y[0] for y in y_train])
      y_train = np.asarray([y[1] for y in y_train])
      y_test_keys = np.asarray([y[0] for y in y_test])
      y_test = np.asarray([y[1] for y in y_test])
[7]: import tensorflow as tf
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense, Dropout
      from tensorflow.keras import regularizers
[8]: X_train.shape
[8]: (6420, 29)
[9]: from sklearn.preprocessing import MinMaxScaler
[10]: scaler = MinMaxScaler()
      X_train = scaler.fit_transform(X_train)
      X_test = scaler.transform(X_test)
[11]: def to_tensor_input(player):
          return scaler.transform(player.values.reshape(-1,29))[0]
[12]: tensor = df.drop(columns=['retroID', 'Pitching'])
      player_tensor_inputs = tensor.apply(lambda player: to_tensor_input(player),__
       ⇒axis=1)
[13]: player_tensor_inputs
              [0.2574, 0.0, 0.0, 0.06256962495358337, 0.0599...
[13]: 0
```

[0.2508, 0.06567164179104477, 0.08196721311475...

```
2
              [0.2447, 0.0, 0.0, 0.06139373684861988, 0.0625...
      3
              [0.2786, 0.11044776119402985, 0.08196721311475...
              [0.2804, 0.09253731343283582, 0.09836065573770...
      8020
              [0.27, 0.08955223880597014, 0.0819672131147541...
      8021
              [0.2717, 0.06865671641791045, 0.04918032786885...
      8022
              [0.2286, 0.0, 0.0, 0.03892808515905434, 0.0342...
              [0.276, 0.026865671641791045, 0.03278688524590...
      8023
              [0.2183, 0.0, 0.0, 0.013491768783265256, 0.011...
      8024
      Length: 8025, dtype: object
[14]: tensor = pd.DataFrame(player_tensor_inputs.values.tolist())
[15]: tensor.to_csv('../core/tensors/t_pitching.csv', index=False, float_format='%g')
[17]: | epochs = 4000
      batch_size = 32
      loss_param = 'mse'
      optimizer_param = 'adam'
      stop_monitor = 'val_loss'
      stop_patience = 50
[18]: from tensorflow.keras.callbacks import EarlyStopping
[19]:
      early_stop = EarlyStopping(monitor=stop_monitor, patience=stop_patience)
[20]: model = Sequential()
      model.add(Dense(29, activation='relu', kernel_regularizer=regularizers.12(0.
       →0001)))
      model.add(Dropout(0.5))
      model.add(Dense(58, activation='relu', kernel_regularizer=regularizers.12(0.
       →0001)))
      model.add(Dropout(0.5))
      model.add(Dense(units=1, activation='sigmoid'))
      model.compile(loss=loss_param, optimizer=optimizer_param)
[21]: results = model.fit(x=X_train, y=y_train,
                              epochs=epochs,
                              batch_size=batch_size,
                              validation_data=(X_test, y_test),
                              callbacks=[early_stop]
                          )
```

```
Train on 6420 samples, validate on 1605 samples
Epoch 1/4000
val_loss: 0.0035
Epoch 2/4000
val_loss: 0.0021
Epoch 3/4000
val_loss: 0.0013
Epoch 4/4000
6420/6420 [============] - Os 49us/sample - loss: 0.0015 -
val_loss: 8.8244e-04
Epoch 5/4000
6420/6420 [============== ] - 0s 46us/sample - loss: 0.0011 -
val_loss: 6.9195e-04
Epoch 6/4000
6420/6420 [============= ] - Os 50us/sample - loss: 9.0205e-04 -
val_loss: 5.2742e-04
Epoch 7/4000
6420/6420 [============= ] - Os 52us/sample - loss: 7.3946e-04 -
val_loss: 4.4965e-04
Epoch 8/4000
val_loss: 4.5362e-04
Epoch 9/4000
6420/6420 [============= ] - Os 53us/sample - loss: 6.3987e-04 -
val_loss: 3.7094e-04
Epoch 10/4000
val_loss: 3.7966e-04
Epoch 11/4000
6420/6420 [============= ] - Os 61us/sample - loss: 5.8589e-04 -
val_loss: 3.5014e-04
Epoch 12/4000
6420/6420 [============= ] - Os 52us/sample - loss: 5.5244e-04 -
val_loss: 3.2501e-04
Epoch 13/4000
val_loss: 3.1699e-04
Epoch 14/4000
6420/6420 [============ ] - Os 50us/sample - loss: 5.2772e-04 -
val_loss: 3.1689e-04
Epoch 15/4000
val_loss: 3.1092e-04
Epoch 16/4000
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val_loss: 3.1406e-04
Epoch 17/4000
6420/6420 [============= ] - Os 68us/sample - loss: 4.8153e-04 -
val_loss: 2.9968e-04
Epoch 18/4000
val_loss: 2.9325e-04
Epoch 19/4000
val_loss: 2.7578e-04
Epoch 20/4000
6420/6420 [============= ] - Os 72us/sample - loss: 4.9546e-04 -
val_loss: 3.3074e-04
Epoch 21/4000
val_loss: 3.0079e-04
Epoch 22/4000
6420/6420 [============] - Os 46us/sample - loss: 4.8102e-04 -
val_loss: 2.7513e-04
Epoch 23/4000
6420/6420 [============= ] - Os 64us/sample - loss: 4.5643e-04 -
val_loss: 2.7033e-04
Epoch 24/4000
val_loss: 2.9084e-04
Epoch 25/4000
val_loss: 2.6616e-04
Epoch 26/4000
val_loss: 2.7724e-04
Epoch 27/4000
6420/6420 [============= ] - Os 53us/sample - loss: 4.5755e-04 -
val_loss: 2.5632e-04
Epoch 28/4000
val_loss: 2.6314e-04
Epoch 29/4000
val_loss: 2.4323e-04
Epoch 30/4000
6420/6420 [============= ] - Os 72us/sample - loss: 4.1988e-04 -
val_loss: 2.4475e-04
Epoch 31/4000
val_loss: 2.6340e-04
Epoch 32/4000
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val_loss: 2.5903e-04
Epoch 33/4000
6420/6420 [=============] - 1s 104us/sample - loss: 4.1919e-04
- val_loss: 2.5305e-04
Epoch 34/4000
6420/6420 [============== ] - 1s 85us/sample - loss: 4.3582e-04 -
val_loss: 2.4753e-04
Epoch 35/4000
val_loss: 2.2769e-04
Epoch 36/4000
6420/6420 [============= ] - Os 59us/sample - loss: 4.4114e-04 -
val_loss: 2.3009e-04
Epoch 37/4000
6420/6420 [============ ] - Os 57us/sample - loss: 4.1271e-04 -
val_loss: 2.6178e-04
Epoch 38/4000
val_loss: 2.3378e-04
Epoch 39/4000
6420/6420 [============= ] - Os 63us/sample - loss: 4.1566e-04 -
val_loss: 2.2211e-04
Epoch 40/4000
val_loss: 2.3926e-04
Epoch 41/4000
val_loss: 2.2952e-04
Epoch 42/4000
val_loss: 2.1442e-04
Epoch 43/4000
6420/6420 [============] - Os 58us/sample - loss: 4.3976e-04 -
val_loss: 2.3676e-04
Epoch 44/4000
6420/6420 [============= ] - Os 54us/sample - loss: 4.1991e-04 -
val_loss: 2.2202e-04
Epoch 45/4000
val_loss: 2.2512e-04
Epoch 46/4000
6420/6420 [============= ] - Os 56us/sample - loss: 4.0262e-04 -
val_loss: 2.2537e-04
Epoch 47/4000
val_loss: 2.1841e-04
Epoch 48/4000
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val_loss: 2.4825e-04
Epoch 49/4000
6420/6420 [============== - - 1s 108us/sample - loss: 4.3170e-04
- val_loss: 2.1427e-04
Epoch 50/4000
val_loss: 2.2604e-04
Epoch 51/4000
- val_loss: 2.0489e-04
Epoch 52/4000
6420/6420 [============= ] - Os 72us/sample - loss: 3.8088e-04 -
val_loss: 2.0127e-04
Epoch 53/4000
val_loss: 2.1046e-04
Epoch 54/4000
6420/6420 [============= ] - Os 64us/sample - loss: 3.9881e-04 -
val_loss: 2.1971e-04
Epoch 55/4000
6420/6420 [============= ] - Os 65us/sample - loss: 3.8779e-04 -
val_loss: 2.2584e-04
Epoch 56/4000
val_loss: 2.0682e-04
Epoch 57/4000
6420/6420 [============] - Os 54us/sample - loss: 4.2708e-04 -
val_loss: 2.3885e-04
Epoch 58/4000
val_loss: 2.7590e-04
Epoch 59/4000
6420/6420 [============= ] - Os 53us/sample - loss: 3.6134e-04 -
val_loss: 2.0648e-04
Epoch 60/4000
val_loss: 2.1653e-04
Epoch 61/4000
val_loss: 1.8850e-04
Epoch 62/4000
6420/6420 [=============] - 1s 111us/sample - loss: 3.9704e-04
- val_loss: 2.1104e-04
Epoch 63/4000
val_loss: 1.9132e-04
Epoch 64/4000
6420/6420 [============= ] - Os 48us/sample - loss: 4.2228e-04 -
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val_loss: 1.9923e-04
Epoch 65/4000
6420/6420 [============= ] - Os 64us/sample - loss: 4.0619e-04 -
val_loss: 1.9194e-04
Epoch 66/4000
val_loss: 1.9624e-04
Epoch 67/4000
val_loss: 2.0513e-04
Epoch 68/4000
6420/6420 [============== ] - Os 53us/sample - loss: 3.6470e-04 -
val_loss: 1.7655e-04
Epoch 69/4000
val_loss: 1.8333e-04
Epoch 70/4000
6420/6420 [============] - Os 55us/sample - loss: 4.3093e-04 -
val_loss: 2.1346e-04
Epoch 71/4000
val_loss: 1.9133e-04
Epoch 72/4000
val_loss: 1.9094e-04
Epoch 73/4000
6420/6420 [============= ] - Os 62us/sample - loss: 3.8602e-04 -
val_loss: 1.8424e-04
Epoch 74/4000
val_loss: 2.0681e-04
Epoch 75/4000
val_loss: 2.1290e-04
Epoch 76/4000
6420/6420 [============= ] - 1s 85us/sample - loss: 3.9244e-04 -
val_loss: 1.9260e-04
Epoch 77/4000
val_loss: 2.0310e-04
Epoch 78/4000
6420/6420 [============ ] - 1s 82us/sample - loss: 3.9858e-04 -
val_loss: 2.3436e-04
Epoch 79/4000
val_loss: 1.9851e-04
Epoch 80/4000
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val_loss: 2.1497e-04
Epoch 81/4000
val_loss: 2.1052e-04
Epoch 82/4000
- val_loss: 1.7637e-04
Epoch 83/4000
- val_loss: 1.8840e-04
Epoch 84/4000
- val_loss: 2.1731e-04
Epoch 85/4000
6420/6420 [============== - - 1s 119us/sample - loss: 3.8175e-04
- val_loss: 2.2192e-04
Epoch 86/4000
6420/6420 [============= ] - 1s 96us/sample - loss: 3.7041e-04 -
val_loss: 1.7459e-04
Epoch 87/4000
6420/6420 [============== ] - 1s 101us/sample - loss: 3.8738e-04
- val_loss: 2.2406e-04
Epoch 88/4000
val_loss: 1.7943e-04
Epoch 89/4000
val_loss: 1.9004e-04
Epoch 90/4000
val_loss: 1.7015e-04
Epoch 91/4000
val_loss: 2.0521e-04
Epoch 92/4000
6420/6420 [============= ] - 1s 92us/sample - loss: 3.7681e-04 -
val_loss: 1.7749e-04
Epoch 93/4000
val_loss: 1.9228e-04
Epoch 94/4000
6420/6420 [=============] - 1s 109us/sample - loss: 3.9241e-04
- val_loss: 2.1736e-04
Epoch 95/4000
val_loss: 1.9194e-04
Epoch 96/4000
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val_loss: 1.7863e-04
Epoch 97/4000
val_loss: 1.7402e-04
Epoch 98/4000
val_loss: 1.9996e-04
Epoch 99/4000
val_loss: 1.6832e-04
Epoch 100/4000
val_loss: 1.7974e-04
Epoch 101/4000
val_loss: 2.1374e-04
Epoch 102/4000
6420/6420 [============] - Os 66us/sample - loss: 4.1230e-04 -
val_loss: 1.9933e-04
Epoch 103/4000
val_loss: 1.8338e-04
Epoch 104/4000
val_loss: 1.8833e-04
Epoch 105/4000
6420/6420 [============] - Os 45us/sample - loss: 3.7677e-04 -
val_loss: 1.6929e-04
Epoch 106/4000
val_loss: 1.8619e-04
Epoch 107/4000
6420/6420 [============= ] - Os 46us/sample - loss: 4.0038e-04 -
val_loss: 1.7728e-04
Epoch 108/4000
val_loss: 1.7525e-04
Epoch 109/4000
val_loss: 1.7394e-04
Epoch 110/4000
6420/6420 [============= ] - Os 49us/sample - loss: 3.7377e-04 -
val_loss: 1.9005e-04
Epoch 111/4000
val_loss: 1.5734e-04
Epoch 112/4000
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val_loss: 1.9043e-04
Epoch 113/4000
val_loss: 1.8249e-04
Epoch 114/4000
val_loss: 2.0348e-04
Epoch 115/4000
val_loss: 2.0192e-04
Epoch 116/4000
6420/6420 [============] - Os 47us/sample - loss: 4.1776e-04 -
val_loss: 1.8761e-04
Epoch 117/4000
val_loss: 1.8552e-04
Epoch 118/4000
6420/6420 [============] - Os 70us/sample - loss: 3.8690e-04 -
val_loss: 1.7253e-04
Epoch 119/4000
6420/6420 [============= ] - Os 67us/sample - loss: 4.0213e-04 -
val_loss: 1.8870e-04
Epoch 120/4000
val_loss: 1.6634e-04
Epoch 121/4000
val_loss: 1.7592e-04
Epoch 122/4000
val_loss: 1.6329e-04
Epoch 123/4000
6420/6420 [============= ] - Os 63us/sample - loss: 3.4388e-04 -
val_loss: 1.7831e-04
Epoch 124/4000
val_loss: 2.1806e-04
Epoch 125/4000
val_loss: 1.8532e-04
Epoch 126/4000
6420/6420 [============= ] - Os 51us/sample - loss: 3.8341e-04 -
val_loss: 1.6547e-04
Epoch 127/4000
val_loss: 1.5375e-04
Epoch 128/4000
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val_loss: 1.8052e-04
Epoch 129/4000
val_loss: 2.4237e-04
Epoch 130/4000
val_loss: 1.5623e-04
Epoch 131/4000
val_loss: 2.1051e-04
Epoch 132/4000
val_loss: 1.5456e-04
Epoch 133/4000
val_loss: 1.8789e-04
Epoch 134/4000
6420/6420 [============= ] - Os 46us/sample - loss: 3.5765e-04 -
val_loss: 1.6933e-04
Epoch 135/4000
val_loss: 1.7699e-04
Epoch 136/4000
val_loss: 1.6628e-04
Epoch 137/4000
6420/6420 [============= ] - Os 45us/sample - loss: 3.9230e-04 -
val_loss: 1.6465e-04
Epoch 138/4000
val_loss: 1.7166e-04
Epoch 139/4000
val_loss: 1.7670e-04
Epoch 140/4000
val_loss: 1.8580e-04
Epoch 141/4000
val_loss: 1.9484e-04
Epoch 142/4000
6420/6420 [============= ] - Os 44us/sample - loss: 3.8097e-04 -
val_loss: 2.1516e-04
Epoch 143/4000
val_loss: 1.8775e-04
Epoch 144/4000
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val_loss: 2.3136e-04
Epoch 145/4000
val_loss: 1.7378e-04
Epoch 146/4000
val_loss: 1.7078e-04
Epoch 147/4000
val_loss: 1.7361e-04
Epoch 148/4000
6420/6420 [============= ] - Os 59us/sample - loss: 4.0065e-04 -
val_loss: 2.1212e-04
Epoch 149/4000
val_loss: 1.9285e-04
Epoch 150/4000
6420/6420 [============] - Os 72us/sample - loss: 3.9891e-04 -
val_loss: 1.7574e-04
Epoch 151/4000
6420/6420 [============= ] - Os 61us/sample - loss: 3.5630e-04 -
val_loss: 1.8421e-04
Epoch 152/4000
val_loss: 1.7520e-04
Epoch 153/4000
val_loss: 1.6459e-04
Epoch 154/4000
val_loss: 1.6536e-04
Epoch 155/4000
6420/6420 [============ ] - Os 73us/sample - loss: 3.6789e-04 -
val_loss: 1.7232e-04
Epoch 156/4000
val_loss: 1.8355e-04
Epoch 157/4000
val_loss: 1.8785e-04
Epoch 158/4000
6420/6420 [============= ] - Os 76us/sample - loss: 3.9953e-04 -
val_loss: 1.8905e-04
Epoch 159/4000
val_loss: 2.1174e-04
Epoch 160/4000
```

```
val_loss: 1.9447e-04
Epoch 161/4000
val_loss: 1.7476e-04
Epoch 162/4000
val_loss: 1.6093e-04
Epoch 163/4000
val_loss: 1.6319e-04
Epoch 164/4000
6420/6420 [============= ] - Os 44us/sample - loss: 3.6413e-04 -
val_loss: 2.0747e-04
Epoch 165/4000
val_loss: 1.5520e-04
Epoch 166/4000
6420/6420 [============= ] - Os 47us/sample - loss: 3.3178e-04 -
val_loss: 1.5067e-04
Epoch 167/4000
6420/6420 [============= ] - Os 45us/sample - loss: 3.6772e-04 -
val_loss: 1.7527e-04
Epoch 168/4000
val_loss: 1.8171e-04
Epoch 169/4000
6420/6420 [============= ] - Os 43us/sample - loss: 4.1335e-04 -
val_loss: 2.5147e-04
Epoch 170/4000
val_loss: 1.7804e-04
Epoch 171/4000
val_loss: 1.5357e-04
Epoch 172/4000
val_loss: 1.6474e-04
Epoch 173/4000
val_loss: 1.7761e-04
Epoch 174/4000
6420/6420 [============ ] - Os 45us/sample - loss: 4.1252e-04 -
val_loss: 1.9731e-04
Epoch 175/4000
val_loss: 1.4349e-04
Epoch 176/4000
```

```
val_loss: 2.0685e-04
Epoch 177/4000
6420/6420 [============= ] - Os 52us/sample - loss: 3.8089e-04 -
val_loss: 1.7820e-04
Epoch 178/4000
val_loss: 1.4901e-04
Epoch 179/4000
val_loss: 1.8517e-04
Epoch 180/4000
val_loss: 1.5498e-04
Epoch 181/4000
val_loss: 1.9027e-04
Epoch 182/4000
6420/6420 [============] - Os 72us/sample - loss: 3.8668e-04 -
val_loss: 1.5464e-04
Epoch 183/4000
val_loss: 1.6829e-04
Epoch 184/4000
val_loss: 2.2951e-04
Epoch 185/4000
6420/6420 [============= ] - Os 66us/sample - loss: 3.7516e-04 -
val_loss: 1.6364e-04
Epoch 186/4000
val_loss: 1.6113e-04
Epoch 187/4000
6420/6420 [============== ] - Os 59us/sample - loss: 4.4246e-04 -
val_loss: 1.6503e-04
Epoch 188/4000
val_loss: 1.9615e-04
Epoch 189/4000
val_loss: 1.9750e-04
Epoch 190/4000
6420/6420 [============= ] - Os 46us/sample - loss: 4.0413e-04 -
val_loss: 1.5363e-04
Epoch 191/4000
val_loss: 1.7732e-04
Epoch 192/4000
```

```
val_loss: 1.6430e-04
Epoch 193/4000
val_loss: 1.7617e-04
Epoch 194/4000
val_loss: 2.2310e-04
Epoch 195/4000
val_loss: 1.6982e-04
Epoch 196/4000
val_loss: 1.4669e-04
Epoch 197/4000
val_loss: 1.4314e-04
Epoch 198/4000
6420/6420 [============= ] - Os 71us/sample - loss: 3.6925e-04 -
val_loss: 1.5511e-04
Epoch 199/4000
val_loss: 1.7227e-04
Epoch 200/4000
val_loss: 1.6129e-04
Epoch 201/4000
6420/6420 [============= ] - Os 50us/sample - loss: 3.7737e-04 -
val_loss: 2.0729e-04
Epoch 202/4000
val_loss: 1.5644e-04
Epoch 203/4000
6420/6420 [============= ] - Os 47us/sample - loss: 3.7491e-04 -
val_loss: 1.5643e-04
Epoch 204/4000
6420/6420 [============= ] - Os 46us/sample - loss: 3.8401e-04 -
val_loss: 1.5636e-04
Epoch 205/4000
val_loss: 1.5338e-04
Epoch 206/4000
6420/6420 [============ ] - Os 53us/sample - loss: 4.1122e-04 -
val_loss: 1.6970e-04
Epoch 207/4000
val_loss: 1.5571e-04
Epoch 208/4000
```

```
val_loss: 1.4740e-04
Epoch 209/4000
- loss: 3.2 - 0s 71us/sample - loss: 3.4491e-04 - val_loss: 1.4933e-04
Epoch 210/4000
val_loss: 1.9531e-04
Epoch 211/4000
val_loss: 1.7508e-04
Epoch 212/4000
6420/6420 [============= ] - Os 75us/sample - loss: 3.6905e-04 -
val_loss: 1.6643e-04
Epoch 213/4000
val_loss: 1.7517e-04
Epoch 214/4000
6420/6420 [============= ] - Os 53us/sample - loss: 4.0734e-04 -
val_loss: 1.9799e-04
Epoch 215/4000
6420/6420 [============= ] - Os 50us/sample - loss: 4.1990e-04 -
val_loss: 1.6936e-04
Epoch 216/4000
val_loss: 1.9487e-04
Epoch 217/4000
6420/6420 [============= ] - Os 49us/sample - loss: 3.9314e-04 -
val_loss: 1.6527e-04
Epoch 218/4000
val_loss: 1.6359e-04
Epoch 219/4000
6420/6420 [============= ] - Os 44us/sample - loss: 3.8098e-04 -
val_loss: 1.6258e-04
Epoch 220/4000
6420/6420 [============= ] - Os 43us/sample - loss: 3.7306e-04 -
val_loss: 1.4014e-04
Epoch 221/4000
val_loss: 1.3826e-04
Epoch 222/4000
6420/6420 [============= ] - Os 46us/sample - loss: 3.6621e-04 -
val_loss: 1.6607e-04
Epoch 223/4000
val_loss: 1.4828e-04
Epoch 224/4000
```

```
val_loss: 1.6845e-04
Epoch 225/4000
6420/6420 [============= ] - Os 51us/sample - loss: 3.6580e-04 -
val_loss: 1.7061e-04
Epoch 226/4000
val_loss: 1.4069e-04
Epoch 227/4000
val_loss: 1.6442e-04
Epoch 228/4000
val_loss: 1.6840e-04
Epoch 229/4000
val_loss: 1.6799e-04
Epoch 230/4000
6420/6420 [============= ] - Os 67us/sample - loss: 3.9271e-04 -
val_loss: 1.7598e-04
Epoch 231/4000
6420/6420 [============= ] - Os 66us/sample - loss: 3.9200e-04 -
val_loss: 1.7821e-04
Epoch 232/4000
val_loss: 1.6983e-04
Epoch 233/4000
val_loss: 1.6949e-04
Epoch 234/4000
val_loss: 2.3774e-04
Epoch 235/4000
6420/6420 [============] - Os 55us/sample - loss: 3.6622e-04 -
val_loss: 1.5798e-04
Epoch 236/4000
val_loss: 1.9084e-04
Epoch 237/4000
val_loss: 1.8301e-04
Epoch 238/4000
6420/6420 [============ ] - Os 73us/sample - loss: 3.6314e-04 -
val_loss: 1.7106e-04
Epoch 239/4000
val_loss: 1.7895e-04
Epoch 240/4000
```

```
val_loss: 1.5395e-04
Epoch 241/4000
6420/6420 [============] - Os 70us/sample - loss: 4.5325e-04 -
val_loss: 2.7468e-04
Epoch 242/4000
val_loss: 2.0811e-04
Epoch 243/4000
val_loss: 1.4190e-04
Epoch 244/4000
val_loss: 1.4648e-04
Epoch 245/4000
val_loss: 1.5179e-04
Epoch 246/4000
6420/6420 [============== ] - Os 44us/sample - loss: 3.8492e-04 -
val_loss: 1.5877e-04
Epoch 247/4000
val_loss: 1.7363e-04
Epoch 248/4000
val_loss: 1.5646e-04
Epoch 249/4000
6420/6420 [============= ] - Os 43us/sample - loss: 3.7851e-04 -
val_loss: 1.9639e-04
Epoch 250/4000
val_loss: 1.6500e-04
Epoch 251/4000
6420/6420 [============] - Os 47us/sample - loss: 4.1462e-04 -
val_loss: 1.8896e-04
Epoch 252/4000
val_loss: 1.4212e-04
Epoch 253/4000
val_loss: 1.5303e-04
Epoch 254/4000
6420/6420 [============= ] - Os 48us/sample - loss: 3.9610e-04 -
val_loss: 1.6398e-04
Epoch 255/4000
val_loss: 1.6363e-04
Epoch 256/4000
```

```
val_loss: 1.5956e-04
Epoch 257/4000
val_loss: 1.4108e-04
Epoch 258/4000
val_loss: 1.5824e-04
Epoch 259/4000
val_loss: 1.6287e-04
Epoch 260/4000
val_loss: 2.1092e-04
Epoch 261/4000
val_loss: 1.4752e-04
Epoch 262/4000
6420/6420 [============= ] - Os 55us/sample - loss: 3.4157e-04 -
val_loss: 1.8513e-04
Epoch 263/4000
6420/6420 [============= ] - Os 50us/sample - loss: 3.7130e-04 -
val_loss: 1.6227e-04
Epoch 264/4000
val_loss: 1.4024e-04
Epoch 265/4000
val_loss: 1.4579e-04
Epoch 266/4000
val_loss: 1.4124e-04
Epoch 267/4000
6420/6420 [============= ] - Os 65us/sample - loss: 3.9763e-04 -
val_loss: 2.0330e-04
Epoch 268/4000
val_loss: 1.8770e-04
Epoch 269/4000
val_loss: 2.0037e-04
Epoch 270/4000
6420/6420 [============= ] - Os 67us/sample - loss: 3.9476e-04 -
val_loss: 1.8254e-04
Epoch 271/4000
val_loss: 1.5522e-04
```

[22]: model.summary() Model: "sequential" Layer (type) Output Shape Param # ______ dense (Dense) multiple 870 _____ multiple dropout (Dropout) dense_1 (Dense) multiple 1740 _____ dropout_1 (Dropout) multiple _____ dense_2 (Dense) multiple ______ Total params: 2,669 Trainable params: 2,669 Non-trainable params: 0 [23]: import os [24]: losses = model.history.history losses['loss'] = np.asarray(losses['loss']) losses['val_loss'] = np.asarray(losses['val_loss']) final_number_of_epochs = len(losses['loss']) min_loss = losses['loss'].min() mean_loss = losses['loss'].mean() final_loss = losses['loss'][-1] min_val_loss = losses['val_loss'].min() mean_val_loss = losses['val_loss'].mean() final_val_loss = losses['val_loss'][-1] def get_model_summary(): output = [] model.summary(print_fn=lambda line: output.append(line)) return str(output).strip('[]') summary = get_model_summary() record = { 'Epochs': final_number_of_epochs, 'Batch_Size': batch_size, 'Loss_Func': loss_param, 'Optimizer': optimizer_param, 'Early_Stop_Monitor': stop_monitor,

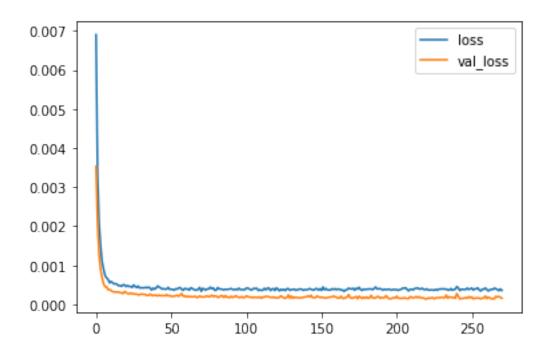
```
'Early_Stop_Patience': stop_patience,
    'Min_Loss': min_loss,
    'Mean_Loss': mean_loss,
    'Final_Loss': final_loss,
    'Min_Val_Loss': min_val_loss,
    'Mean_Val_Loss': mean_val_loss,
    'Final_Val_Loss': final_val_loss,
    'Model': summary
}
new_data = pd.DataFrame(record, index=[0])
if os.path.exists('../core/records/pitching_results.csv'):
    df_records = pd.read_csv('../core/records/pitching_results.csv')
    df_records = df_records.append(new_data)
else:
    df_records = pd.DataFrame(new_data)
df_records.to_csv('../core/records/pitching_results.csv', index=False,_
 →float_format='%g')
```

Model Evaluation

```
[25]: losses = pd.DataFrame(model.history.history)
```

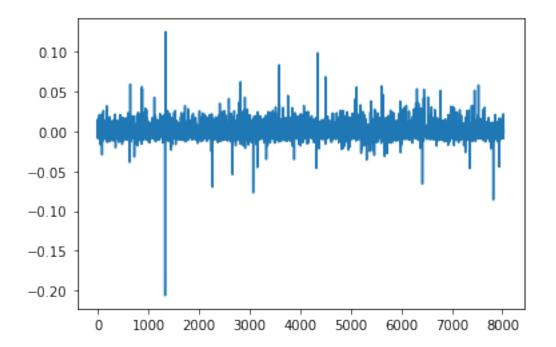
```
[26]: losses.plot()
```

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x145c796d0>



```
[27]: predictions = model.predict(X_test)
      predictions = [pred for sublist in predictions for pred in sublist]
[28]: test_player_ratings = dict(zip(X_test_keys, predictions))
[29]: player_key = df['retroID']
[30]: player_key
[30]: 0
              aardd001
              aased001
      1
      2
              abadf001
      3
              abbog001
      4
              abboj001
              zolds101
      8020
      8021
              zubeb101
              zumaj001
      8022
      8023
              zuveg101
      8024
              zycht001
      Name: retroID, Length: 8025, dtype: object
[31]: results = model.predict(tensor.to_numpy())
[32]: len(results)
[32]: 8025
[33]: results.mean()
[33]: 0.6065751
[34]: df['Pitching'].shape
[34]: (8025,)
[35]: results.shape
[35]: (8025, 1)
[36]: results = [pred for sublist in results for pred in sublist]
[37]: diff = df['Pitching'] - results
[38]: diff.plot()
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x14684bd90>



[39]: diff.mean()

[39]: -0.0009138342898704561

[]: