05_All_Models

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0.1 All in one

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- Course: *Introduction to Deep Learning & Neural Networks with Keras*
- Final Project: Build a Regression Model in Keras - All models with comparison

Custom extension combining all models in one notebook

[1]:
```
import pp_utils as pp
```

```
Using TensorFlow backend.
```

0.1.1 1.1. Download, load and clean the data

[2]:
```
import pandas as pd
import numpy as np
```

[3]:
```
# df_concrete_data = pd.read_csv('https://s3-api.us-geo.objectstorage.softlayer.
↪net/cf-courses-data/CognitiveClass/DL0101EN/labs/data/concrete_data.csv')

df_concrete_data = pd.read_csv("./concrete_data.csv")
df_concrete_data.head(7)
```

[3]:

	Cement	Blast Furnace Slag	Fly Ash	Water	Superplasticizer	Coarse Aggregate	Fine Aggregate	Age	Strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.99
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.89
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270	40.27
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365	41.05
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360	44.30
5	266.0	114.0	0.0	228.0	0.0	932.0	670.0	90	47.03
6	380.0	95.0	0.0	228.0	0.0	932.0	594.0	365	43.70

```
3            932.0           594.0  365     41.05
4            978.4           825.5  360     44.30
5            932.0           670.0   90     47.03
6            932.0           594.0  365     43.70
```

[4]:
```
df_concrete_data.describe()
```

[4]:
```
            Cement  Blast Furnace Slag      Fly Ash        Water  \
count  1030.000000         1030.000000  1030.000000  1030.000000
mean    281.167864           73.895825    54.188350   181.567282
std     104.506364           86.279342    63.997004    21.354219
min     102.000000            0.000000     0.000000   121.800000
25%     192.375000            0.000000     0.000000   164.900000
50%     272.900000           22.000000     0.000000   185.000000
75%     350.000000          142.950000   118.300000   192.000000
max     540.000000          359.400000   200.100000   247.000000

       Superplasticizer  Coarse Aggregate  Fine Aggregate          Age  \
count       1030.000000       1030.000000     1030.000000  1030.000000
mean           6.204660        972.918932      773.580485    45.662136
std            5.973841         77.753954       80.175980    63.169912
min            0.000000        801.000000      594.000000     1.000000
25%            0.000000        932.000000      730.950000     7.000000
50%            6.400000        968.000000      779.500000    28.000000
75%           10.200000       1029.400000      824.000000    56.000000
max           32.200000       1145.000000      992.600000   365.000000

          Strength
count  1030.000000
mean     35.817961
std      16.705742
min       2.330000
25%      23.710000
50%      34.445000
75%      46.135000
max      82.600000
```

[5]:
```
# Any null value?
df_concrete_data.isnull().sum()
# ... No, good.
```

[5]:
```
Cement               0
Blast Furnace Slag   0
Fly Ash              0
Water                0
Superplasticizer     0
Coarse Aggregate     0
```

```
Fine Aggregate        0
Age                   0
Strength              0
dtype: int64
```

0.1.2 1.2. Split data into predictors and target

[6]:
```
## Exclude columns 'Age', 'Strength' for predictors
df_predictors = df_concrete_data[df_concrete_data.columns.difference(['Age',␣
↪'Strength'])]

df_target = df_concrete_data['Strength']
```

0.1.3 1.3. Normalizing

[7]:
```
df_predictors_norm = (df_predictors - df_predictors.mean()) / df_predictors.
↪std()
df_predictors_norm.head()
```

[7]:

	Blast Furnace Slag	Cement	Coarse Aggregate	Fine Aggregate	Fly Ash	Superplasticizer	Water
0	-0.856472	2.476712	0.862735	-1.217079	-0.846733	-0.620147	-0.916319
1	-0.856472	2.476712	1.055651	-1.217079	-0.846733	-0.620147	-0.916319
2	0.795140	0.491187	-0.526262	-2.239829	-0.846733	-1.038638	2.174405
3	0.795140	0.491187	-0.526262	-2.239829	-0.846733	-1.038638	2.174405
4	0.678079	-0.790075	0.070492	0.647569	-0.846733	-1.038638	0.488555

[8]:
```
n_cols = df_predictors_norm.shape[1]  # == df_predictors
n_cols # number of predictors
```

[8]:
```
7
```

0.1.4 1.4. Baseline model

[9]:
```
model = pp.regression_model(n_cols, nodes_per_hlayer=[10]) #
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 10)                80
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 11
=================================================================
Total params: 91
Trainable params: 91
Non-trainable params: 0
_________________________________________________________________
```

[10]:
```
mse_ary = pp.train_eval_loop(n_cols, df_predictors, df_target, N=50, epochs=50,␣
↪n_p_hl=[10])
```

```
WARNING: Logging before flag parsing goes to stderr.
W0322 10:54:52.626319 140020835665728 deprecation_wrapper.py:119] From /home/pas
cal/Projects/ML_DL/anaconda3/envs/tensorflow_keras_gpuenv/lib/python3.7/site-
packages/keras/backend/tensorflow_backend.py:422: The name tf.global_variables
is deprecated. Please use tf.compat.v1.global_variables instead.


Iteration:  0 / MSE: 202.42301
Iteration:  1 / MSE: 207.01059
Iteration:  2 / MSE: 863.05018
Iteration:  3 / MSE: 989.06217
Iteration:  4 / MSE: 442.04138
Iteration:  5 / MSE: 264.72076
Iteration:  6 / MSE: 882.24851
Iteration:  7 / MSE: 1070.05195
Iteration:  8 / MSE: 2901.14574
Iteration:  9 / MSE: 1410.57777
Iteration: 10 / MSE: 284.27646
Iteration: 11 / MSE: 189.79941
Iteration: 12 / MSE: 217.81692
Iteration: 13 / MSE: 212.05040
Iteration: 14 / MSE: 543.69669
Iteration: 15 / MSE: 888.38757
Iteration: 16 / MSE: 209.09156
Iteration: 17 / MSE: 198.92263
Iteration: 18 / MSE: 352.88271
Iteration: 19 / MSE: 179.08937
Iteration: 20 / MSE: 193.44001
Iteration: 21 / MSE: 222.95358
Iteration: 22 / MSE: 518.19559
Iteration: 23 / MSE: 434.10038
Iteration: 24 / MSE: 187.61384
```

```
Iteration: 25 / MSE: 1175.52184
Iteration: 26 / MSE: 512.25190
Iteration: 27 / MSE: 195.75329
Iteration: 28 / MSE: 314.21132
Iteration: 29 / MSE: 262.76495
Iteration: 30 / MSE: 181.70890
Iteration: 31 / MSE: 218.84691
Iteration: 32 / MSE: 267.09893
Iteration: 33 / MSE: 283.97599
Iteration: 34 / MSE: 274.36455
Iteration: 35 / MSE: 211.54659
Iteration: 36 / MSE: 482.69262
Iteration: 37 / MSE: 2520.51169
Iteration: 38 / MSE: 296.34462
Iteration: 39 / MSE: 272.58127
Iteration: 40 / MSE: 207.80625
Iteration: 41 / MSE: 180.70865
Iteration: 42 / MSE: 183.58487
Iteration: 43 / MSE: 1565.28432
Iteration: 44 / MSE: 195.90735
Iteration: 45 / MSE: 281.41503
Iteration: 46 / MSE: 190.92395
Iteration: 47 / MSE: 181.68442
Iteration: 48 / MSE: 249.18761
Iteration: 49 / MSE: 232.63365
```

[11]:
```
np_ary = pp.summary(mse_ary, label="baseline model")
```

```
Summary baseline model:
mean(MSE): 500.07921 / unbiased std(MSE): 568.30815 / biased std(MSE): 562.59636
```

[12]:
```
pp.summary_ext(np_ary)
```

```
max: 2901.14574 at epoch:  8 / min: 179.08937 at epoch: 19
```

[13]:
```
df = pp.save_df(np_ary, label='mse_01_bl', fname='11_baseline_model.csv')
df.head()
```

[13]:

	mse_01_bl
0	202.423013
1	207.010588
2	863.050178
3	989.062165
4	442.041380

0.1.5 1.5. Normalized model

[14]:
```
mse_norm_ary = pp.train_eval_loop(n_cols, df_predictors_norm, df_target, N=50,␣
↪epochs=50, n_p_hl=[10])
```

```
Iteration:  0 / MSE: 293.29944
Iteration:  1 / MSE: 345.92081
Iteration:  2 / MSE: 426.86051
Iteration:  3 / MSE: 325.80493
Iteration:  4 / MSE: 375.27394
Iteration:  5 / MSE: 334.33579
Iteration:  6 / MSE: 354.35690
Iteration:  7 / MSE: 644.32649
Iteration:  8 / MSE: 303.00841
Iteration:  9 / MSE: 373.95550
Iteration: 10 / MSE: 372.20734
Iteration: 11 / MSE: 661.10783
Iteration: 12 / MSE: 310.83496
Iteration: 13 / MSE: 442.80741
Iteration: 14 / MSE: 547.19272
Iteration: 15 / MSE: 309.44402
Iteration: 16 / MSE: 473.45867
Iteration: 17 / MSE: 404.20898
Iteration: 18 / MSE: 434.58824
Iteration: 19 / MSE: 416.78042
Iteration: 20 / MSE: 530.71526
Iteration: 21 / MSE: 302.75864
Iteration: 22 / MSE: 331.99026
Iteration: 23 / MSE: 305.50828
Iteration: 24 / MSE: 425.32036
Iteration: 25 / MSE: 468.88989
Iteration: 26 / MSE: 292.18708
Iteration: 27 / MSE: 477.69946
Iteration: 28 / MSE: 404.49376
Iteration: 29 / MSE: 486.57351
Iteration: 30 / MSE: 348.79886
Iteration: 31 / MSE: 341.77660
Iteration: 32 / MSE: 672.20691
Iteration: 33 / MSE: 325.01175
Iteration: 34 / MSE: 293.64973
Iteration: 35 / MSE: 397.03437
Iteration: 36 / MSE: 423.76931
Iteration: 37 / MSE: 356.52585
Iteration: 38 / MSE: 298.73779
Iteration: 39 / MSE: 424.65783
Iteration: 40 / MSE: 303.00100
Iteration: 41 / MSE: 425.04084
```

```
Iteration: 42 / MSE: 335.85895
Iteration: 43 / MSE: 407.88520
Iteration: 44 / MSE: 363.14516
Iteration: 45 / MSE: 311.90181
Iteration: 46 / MSE: 339.57113
Iteration: 47 / MSE: 408.05288
Iteration: 48 / MSE: 381.67831
Iteration: 49 / MSE: 318.20157
```

[15]:
```
np_norm_ary = pp.summary(mse_norm_ary, label="normalized model")
```

```
Summary normalized model:
mean(MSE): 393.04831 / unbiased std(MSE): 93.18617 / biased std(MSE): 92.24960
```

[16]:
```
pp.summary_ext(np_norm_ary)
```

```
max: 672.20691 at epoch: 32 / min: 292.18708 at epoch: 26
```

[17]:
```
df = pp.save_df(np_norm_ary, label='mse_02_norm', fname='12_normalized_model.
↪csv',
                prev_csv='11_baseline_model.csv', prev_df=df)
```

0.1.6 1.6. Normalized model with 100 epochs

[18]:
```
mse_norm100_ary = pp.train_eval_loop(n_cols, df_predictors_norm, df_target,␣
↪N=50, epochs=100, n_p_hl=[10])
```

```
Iteration:  0 / MSE: 243.06795
Iteration:  1 / MSE: 240.88377
Iteration:  2 / MSE: 206.74328
Iteration:  3 / MSE: 221.47607
Iteration:  4 / MSE: 216.30225
Iteration:  5 / MSE: 210.63183
Iteration:  6 / MSE: 209.55883
Iteration:  7 / MSE: 218.93233
Iteration:  8 / MSE: 208.34282
Iteration:  9 / MSE: 219.72780
Iteration: 10 / MSE: 203.61642
Iteration: 11 / MSE: 221.25967
Iteration: 12 / MSE: 212.19008
Iteration: 13 / MSE: 230.78437
Iteration: 14 / MSE: 223.10228
Iteration: 15 / MSE: 219.27893
Iteration: 16 / MSE: 208.73732
Iteration: 17 / MSE: 222.62194
Iteration: 18 / MSE: 210.37689
Iteration: 19 / MSE: 229.44040
```

```
Iteration: 20 / MSE: 225.77407
Iteration: 21 / MSE: 213.58242
Iteration: 22 / MSE: 237.53782
Iteration: 23 / MSE: 224.75938
Iteration: 24 / MSE: 216.31853
Iteration: 25 / MSE: 201.43080
Iteration: 26 / MSE: 227.58923
Iteration: 27 / MSE: 217.95289
Iteration: 28 / MSE: 217.37822
Iteration: 29 / MSE: 252.25120
Iteration: 30 / MSE: 239.42162
Iteration: 31 / MSE: 222.96539
Iteration: 32 / MSE: 203.78414
Iteration: 33 / MSE: 219.23929
Iteration: 34 / MSE: 227.25704
Iteration: 35 / MSE: 211.43180
Iteration: 36 / MSE: 231.11931
Iteration: 37 / MSE: 225.01018
Iteration: 38 / MSE: 210.37566
Iteration: 39 / MSE: 210.35426
Iteration: 40 / MSE: 218.36043
Iteration: 41 / MSE: 215.91941
Iteration: 42 / MSE: 230.11748
Iteration: 43 / MSE: 205.79561
Iteration: 44 / MSE: 208.38061
Iteration: 45 / MSE: 232.86975
Iteration: 46 / MSE: 244.94528
Iteration: 47 / MSE: 211.44748
Iteration: 48 / MSE: 214.29584
Iteration: 49 / MSE: 213.74311
```

[19]:
```
np_norm100_ary = pp.summary(mse_norm100_ary, label="normalized 100 epoch model")
```

```
Summary normalized 100 epoch model:
mean(MSE): 220.16967 / unbiased std(MSE): 11.63943 / biased std(MSE): 11.52245
```

[20]:
```
pp.summary_ext(np_norm100_ary)
```

```
max: 252.25120 at epoch: 29 / min: 201.43080 at epoch: 25
```

[21]:
```
df = pp.save_df(np_norm100_ary, label='mse_03_norm100',␣
↪fname='13_normalized_100eoch_model.csv',
                prev_csv='12_normalized_model.csv', prev_df=df)
```

0.1.7 1.7. Normalized model with 3 hidden layers

[22]:
```
model = pp.regression_model(n_cols, nodes_per_hlayer=[10, 10, 10]) #
model.summary()
```

```
Model: "sequential_152"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_303 (Dense)            (None, 10)                80
_________________________________________________________________
dense_304 (Dense)            (None, 10)                110
_________________________________________________________________
dense_305 (Dense)            (None, 10)                110
_________________________________________________________________
dense_306 (Dense)            (None, 1)                 11
=================================================================
Total params: 311
Trainable params: 311
Non-trainable params: 0
_________________________________________________________________
```

[23]:
```
mse_norm_3hl_ary = pp.train_eval_loop(n_cols, df_predictors_norm, df_target,␣
↪N=50, epochs=50,
                                      n_p_hl=[10, 10, 10])
```

```
Iteration:  0 / MSE: 197.96650
Iteration:  1 / MSE: 195.65100
Iteration:  2 / MSE: 185.91332
Iteration:  3 / MSE: 197.41985
Iteration:  4 / MSE: 198.25296
Iteration:  5 / MSE: 190.22290
Iteration:  6 / MSE: 197.80909
Iteration:  7 / MSE: 190.57817
Iteration:  8 / MSE: 203.12779
Iteration:  9 / MSE: 189.12403
Iteration: 10 / MSE: 192.13600
Iteration: 11 / MSE: 186.14364
Iteration: 12 / MSE: 167.82419
Iteration: 13 / MSE: 189.29370
Iteration: 14 / MSE: 190.28790
Iteration: 15 / MSE: 190.00143
Iteration: 16 / MSE: 198.90881
Iteration: 17 / MSE: 192.71368
Iteration: 18 / MSE: 196.83225
Iteration: 19 / MSE: 193.58226
Iteration: 20 / MSE: 183.20690
```

```
Iteration: 21 / MSE: 189.67665
Iteration: 22 / MSE: 194.12626
Iteration: 23 / MSE: 200.25488
Iteration: 24 / MSE: 193.20345
Iteration: 25 / MSE: 190.28230
Iteration: 26 / MSE: 185.49285
Iteration: 27 / MSE: 196.87226
Iteration: 28 / MSE: 190.29386
Iteration: 29 / MSE: 184.84795
Iteration: 30 / MSE: 191.40140
Iteration: 31 / MSE: 180.61910
Iteration: 32 / MSE: 196.98983
Iteration: 33 / MSE: 198.39854
Iteration: 34 / MSE: 184.69085
Iteration: 35 / MSE: 193.99796
Iteration: 36 / MSE: 195.47900
Iteration: 37 / MSE: 194.88887
Iteration: 38 / MSE: 190.58172
Iteration: 39 / MSE: 180.55547
Iteration: 40 / MSE: 196.32998
Iteration: 41 / MSE: 197.91852
Iteration: 42 / MSE: 194.84702
Iteration: 43 / MSE: 201.94220
Iteration: 44 / MSE: 201.67272
Iteration: 45 / MSE: 193.52697
Iteration: 46 / MSE: 195.14519
Iteration: 47 / MSE: 190.99538
Iteration: 48 / MSE: 167.04014
Iteration: 49 / MSE: 198.64392
```

[24]:
```
np_norm_3hl_ary = pp.summary(mse_norm_3hl_ary, label="normalized 3 hidden␣
↪layers model")
```

```
Summary normalized 3 hidden layers model:
mean(MSE): 191.95423 / unbiased std(MSE): 7.35910 / biased std(MSE): 7.28514
```

[25]:
```
pp.summary_ext(np_norm_3hl_ary)
```

```
max: 203.12779 at epoch:  8 / min: 167.04014 at epoch: 48
```

[26]:
```
df = pp.save_df(np_norm_3hl_ary, label='mse_04_norm_3hl',␣
↪fname='14_normalized_3hl_model.csv',
                prev_csv='13_normalized_100eoch_model.csv', prev_df=df)
```

0.1.8 1.8. Results comparison

1 - Comparison normalized model (B) to baseline model (A)

- the MSE is *less* (therefore better) for the normalized model (B).
- Also the spread for the normalized model, as measured by standard deviation, is *less* (less variability) than it is for the baseline model.
- Here normalization does seem to improve the performance in term of:
  - mean (although not by that much in this case) and
  - standard deviation.

2 - Comparison normalized model with 100 epochs (C) to normalized model (B) and baseline model (A)

- More iterations does improve significantly both the mean of MSE and (reduce) the spread (standard deviation) compare to both previous normalized model (with 50 epochs) and the baseline model.

3 -Comparison normalized model with 3 hidden layers to normalized model (B).

- More (hidden) layers does improve (even more) the mean MSE and the spread compare to all previous models.

0.1.9 1.9. Summary

[27]:
```
df.head()
```

[27]:

	mse_01_bl	mse_02_norm	mse_03_norm100	mse_04_norm_3hl
0	202.423013	293.299437	243.067954	197.966500
1	207.010588	345.920812	240.883772	195.650999
2	863.050178	426.860508	206.743278	185.913316
3	989.062165	325.804934	221.476072	197.419849
4	442.041380	375.273944	216.302253	198.252957

[28]:
```
df.describe()
```

[28]:

	mse_01_bl	mse_02_norm	mse_03_norm100	mse_04_norm_3hl
count	50.000000	50.000000	50.000000	50.000000
mean	500.079213	393.048313	220.169670	191.954232
std	568.308148	93.186171	11.639429	7.359100
min	179.089366	292.187082	201.430804	167.040144
25%	203.569907	325.210044	210.831826	189.757842
50%	265.909847	373.081419	218.646379	193.365210
75%	504.862077	425.250476	226.886297	196.960436
max	2901.145737	672.206907	252.251195	203.127785

[29]:
```
df.shape
```

[29]:
```
(50, 4)
```

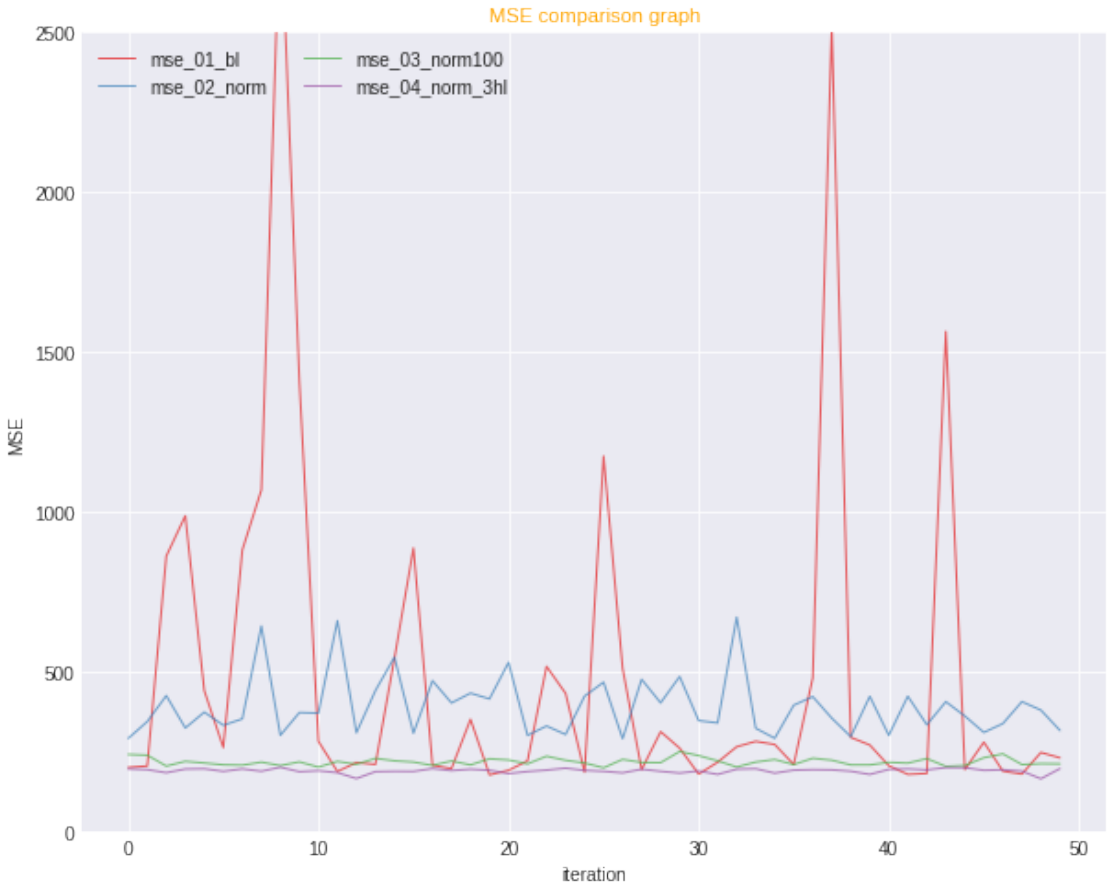
[30]:
```
df.columns
```

[30]:
```
Index(['mse_01_bl', 'mse_02_norm', 'mse_03_norm100', 'mse_04_norm_3hl'],
dtype='object')
```

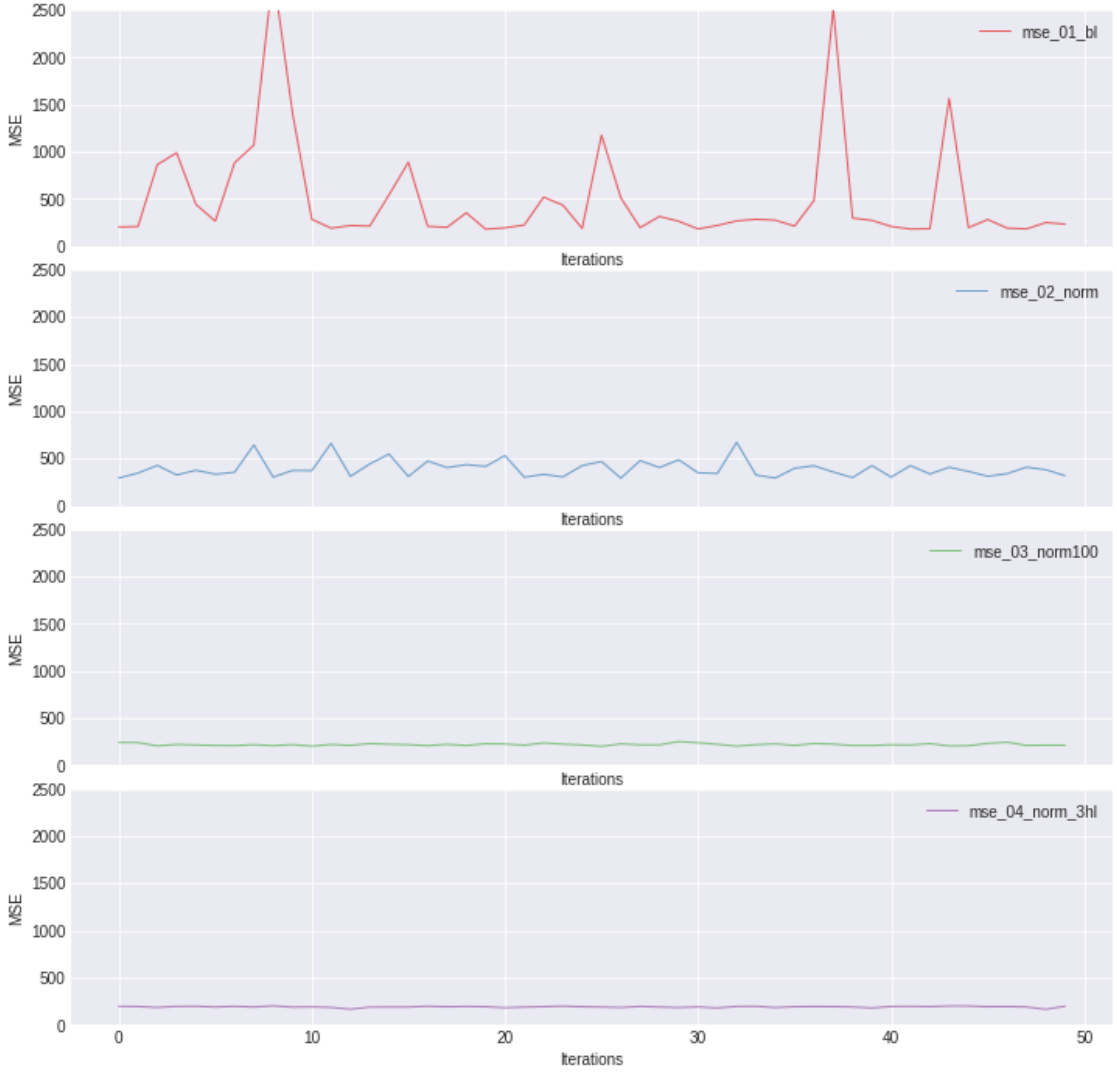
[31]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

[32]:
```
fig = plt.figure(figsize=(10, 8))

# style
plt.style.use('seaborn-darkgrid')

# create a color palette
palette = plt.get_cmap('Set1')

# multiple lines plot
plt.ylim(0, 2500)
ixes = list(range(0, df.shape[0]))
for ix, col in enumerate(df):
  plt.plot(ixes, df[col], marker='', color=palette(ix), linewidth=1, alpha=0.7,
           label=df.columns[ix])

# Add legend
plt.legend(loc=2, ncol=2)

# Add titles
plt.title("MSE comparison graph", loc='center', fontsize=11, fontweight=0,␣
 ↪color='orange')
plt.xlabel("iteration")
plt.ylabel("MSE")
```

[32]:
```
Text(0, 0.5, 'MSE')
```



[33]:
```
fig, axs = plt.subplots(4, 1, sharex=True, sharey=True, figsize=(12, 12),
                        gridspec_kw={'hspace': 0.1, 'wspace': 0.2})

ixes = list(range(0, df.shape[0]))
plt.ylim(0, 2500)
for ix, col in enumerate(df):
  ax = axs[ix]
  ax.plot(ixes, df[col], marker='', color=palette(ix), linewidth=1, alpha=0.7,
          label=df.columns[ix])

  ax.set_xlabel('Iterations')
  ax.set_ylabel('MSE')
  ax.legend(loc="upper right")
```


mse_01_bl
mse_02_norm
mse_03_norm100
mse_04_norm_3hl
MSE
Iterations
0
500
1000
1500
2000
2500
0
10
20
30
40
50

[ ]: