



Universidad Politécnica de Madrid

ESCUELA TÉCNICA SUPERIOR DE INGENIEROS INDUSTRIALES MÁSTER EN AUTOMÁTICA Y ROBÓTICA

APPLIED ARTIFICIAL INTELLIGENCE

Assignment 5.2: MLP for Function Generalization

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MLP for Function Generalisation

1.1 Exercise 1

Choose an adequate MLP structure and training set. Plot in the same figure the training set, the output of the MLP for the test set, and the ground truth sin(x) function.

First of all it is necessary to plot the training data as well as the expected solution (which in this case is known: sin(x) between $[0, 2\pi]$. In this way, thanks to the use of Matlab, Figure 1 has been obtained.

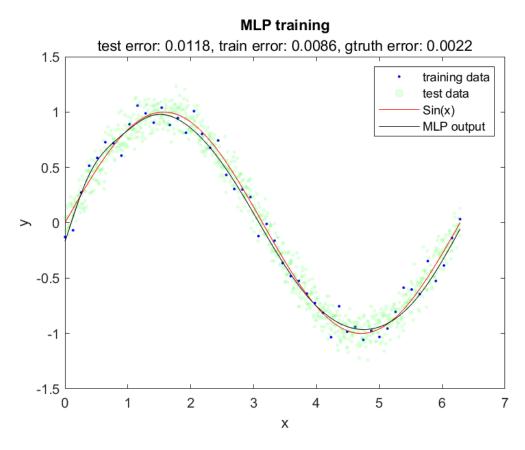


Figure 1: Multi Layer Perceptron (MLP) training with Matlab. In blue the training data (50 values); in green the test data (1000 values); in red the "ground truth" (desired solution) and finally in black the output of the MLP trained with 4 neurons in the hidded layer. The errors are compiled in the subtitle.

The initial structure chosen consists of four neurons in the hidden layer of the network. Further experiments will allow us to conclude which dataset and which architecture is most suitable for this problem. It is worth mentioning that Matlab offers functions that are very convenient for a fast deployment of the neural network,

but they do not allow the desired flexibility. For example, in the following section, we wish to study the evolution of the error as the number of neurons increases. For this particular case, it is to be expected to see the **overfitting** that occurs when the number of neurons is excessive. However, this overfitting should be accompanied by a decreasing training error, which is not observed. We have tried to increase the number of **epochs** but this is only a limit, it is Matlab and its implementation of training that decides when to stop training depending on several other parameters not covered in the course.

Thanks to the Matlab visualisation tool, the structure is easily visible, resulting in the image shown in Figure 2.

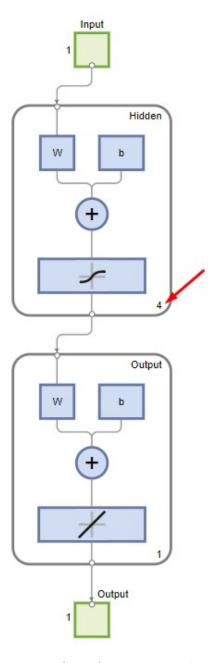


Figure 2: Multi Layer Perceptron (MLP) structure. The number of neurons chosen is marked in red with an arrow.

1.2 Exercise 2

Evaluate the evolution of the train error, the test error and the ground truth error in the following cases:

This is the most experimental part and has already been advanced in the previous section. The order of the sections has been slightly varied, with **the first section** being the study of training with an increasing number of neurons (when in fact it should be the last). We believe that this variation in order is not a problem for the study in question.

1.2.1 Part 1

Changing the net structure: number of neurons.

Figure 3 shows the graph with the results of the experiment. In particular, the three errors can be seen: training error, test error and ground truth error. And this for an increasing number of neurons (from 1 to 50).

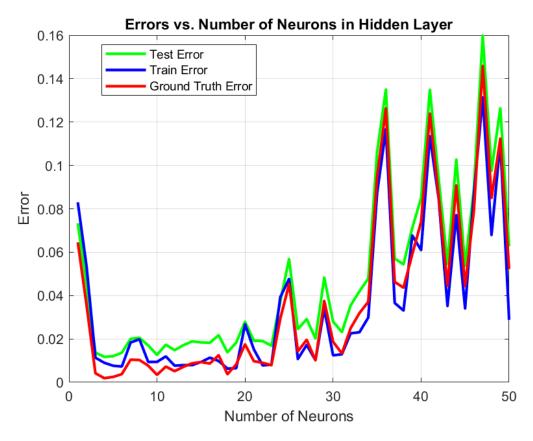


Figure 3: Mean error over five tries evolution with increasing number of neurons in the hidden layer of the network.

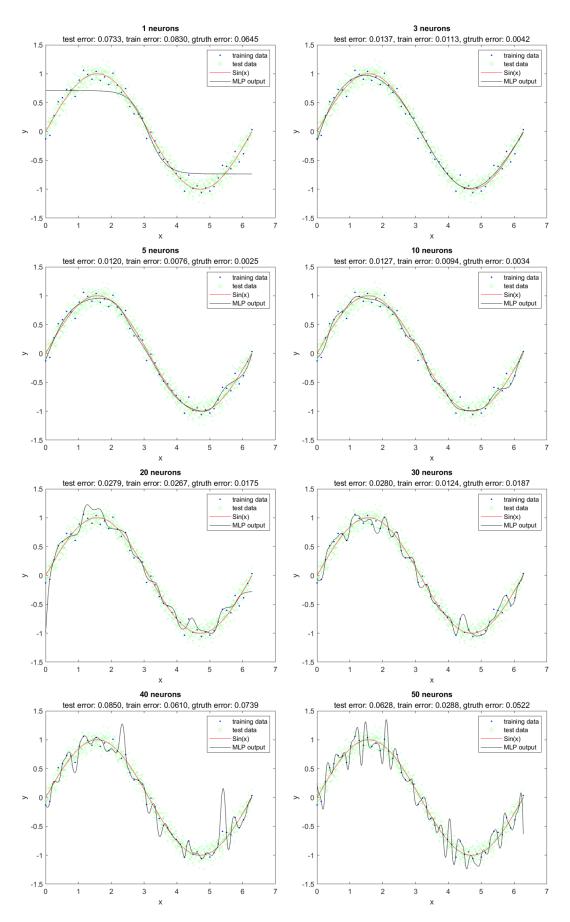


Figure 4: Network outputs for test values according to the number of neurons with which they have been trained (from 1 to 50).

In general, the behaviour is not as expected. One would expect that as the number of neurons increases, the training error should decrease to zero. Attempts have been made to remedy this by increasing the number of **epochs** but this is simply a maximum, not a minimum, so it is really Matlab that given several criteria (not just one) decides to terminate the training. This is done to optimise the training, but in our case it does not allow us to reproduce what we want.

On the other hand, it can be seen that increasing the number of neurons is not always good. In fact, in this case, with 4 or 5 neurons the best results are achieved, and increasing or decreasing the number of neurons is detrimental. We believe that this study may be necessary in general for each problem, in order to obtain an intuition about the size of the network needed to capture the behaviour of the data.

For this part, the following hyperparameters have been selected:

- Training function: trainlm (Levenberg-Marquardt)
- Desired number of epochs: 100
- Performance function: Mean Squared Error (MSE)
- Performance target value: 0
- μ (target value): 1e + 10
- Gradient (target value): 1e 07

1.2.2 Part 2

Changing the training data: number of samples.

In a similar way to the previous section, we iterate the training of the MLP but this time increasing the number of training data. We start with 5 data equispaced between 0 and 2π until we end up with 100 data. The training was repeated 5 times and the average of the five iterations was calculated.

A similar behaviour to that expected is observed in Figure 5 in which the test error instead has a slight increase until it stagnates around 0.01 while the error of the desired (or real - ground truth) data decreases until it is almost zero. Contrary to what is desired, the training error does not start with a zero value and we do not know why. It is true that as the number of data increases, the error decreases rapidly and shows the described behaviour of a slight increase.

- Training function: trainlm (Levenberg-Marquardt)
- Desired number of epochs: 50
- Performance function: Mean Squared Error (MSE)

- Performance target value: 0
- Max fail (Maximum Number of Validation Increases): 50
- Gradient (min target value): 1e 10



Figure 5: Mean error over five tries evolution with increasing number of samples in the training set.

Figure 6 shows different phases of training for an increasing number of samples. Interestingly, with only five samples the neural network is not able to memorise the data (which is very surprising and anomalous), but with 25 samples it behaves as expected.

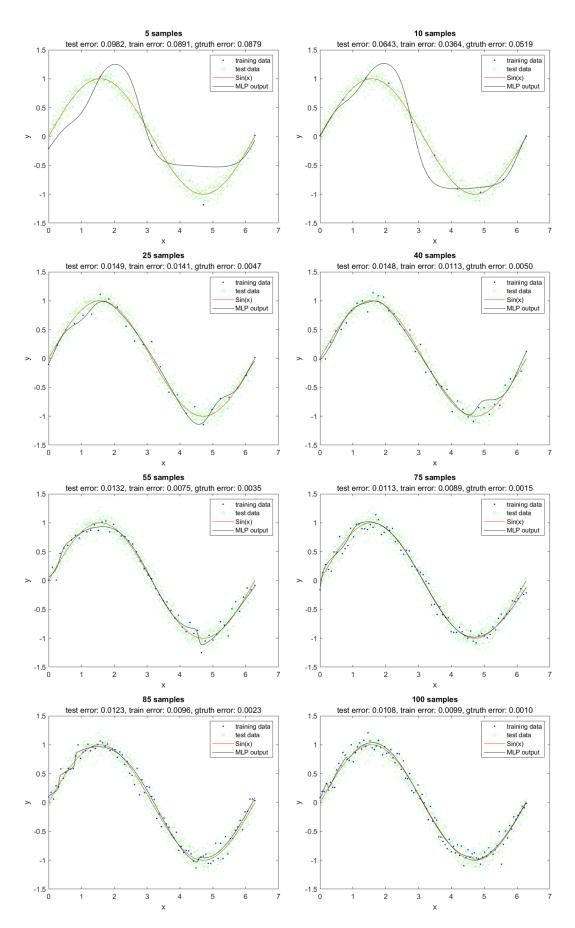


Figure 6: Network outputs for test values according to the number of samples used in the training.

1.2.3 Part 3

Changing the training parameters: initial values, number of epochs, optimisation algorithm, etc.

Finally, we proceed to study how the initialisation of the training affects it. In other words, in the optimisation process, the initial values condition to a large extent the obtaining of global or local optima.

To test this, we proceeded to create a network with the same structure as in the previous section and repeat the training and validation process 100 times. The result can be seen in Figure 7.

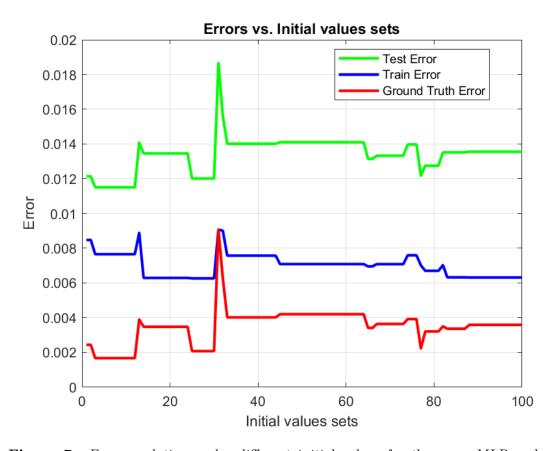


Figure 7: Error evolution under different initial values for the same MLP and same training and test data.

We have repeated the experiment, but this time including in the iterations the creation of the network itself. The results are shown in Figure 8. It can be seen that the errors are higher and that there is a greater variability in each iteration. Except for the increase in computation time, we do not know the underlying reason, which could be, among others, that the creation of the network involves the randomness of many other parameters that for Figure 7 are fixed and only the initial values are modified.

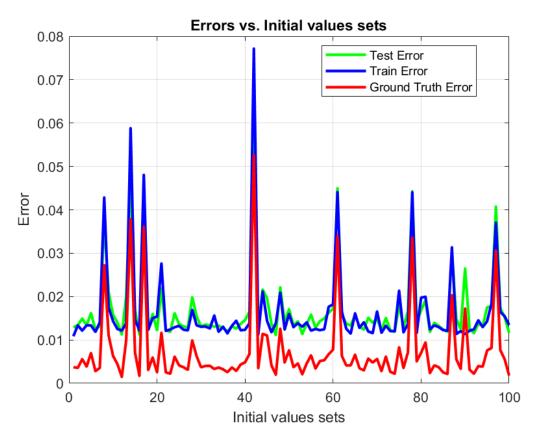


Figure 8: Network outputs for test values according to the number of samples used in the training.

1.3 Relevant Code

The code prepared for this assignment is shown in the next pages in a wider style.

```
2
  %
                            Master in Robotics
3 | %
                      Applied Artificial Intelligence
4
5
  % Assinment 5.2: Function Generalization - MLP
6 % Student: Josep Barbera Civera
  % ID: 17048
  |% Date: 14/04/2024
9
  10
11 | % 1.- Choose an adequate MLP structure and training set.
12
     Plot in the same figure the training set, the output of the MLP
13 | %
      for the test set, and the ground truth sin function.
14
15 \ Evaluate the evolution of the train error, the test error and
16 | %
      the ground truth error in the following cases:
17 | %
18 \mid \% 2. - Changing the training parameters:
19 | %
      initial values, (# of epochs, optimization algorithm)
20 | %
21 | % 3. - Changing the training data:
22 | %
     # of samples (order of samples)
23 | %
24 \mid % 4. - Changing the net structure:
25 % # of neurons
26
28
  % 1. Training set, MLP structure and initial plots
30 | generate_data = false;
                                    %%%%% <- change here as needed!
     %%%%%
31 | plot_specific_MLP_training = false; %%%%% <- change here as needed!
     %%%%%
32 | if (generate_data)
33
      %% Training data (N_train, x_train, y_train)
34
      N_{train} = 50;
35
      x_train = linspace(0, 2*pi, N_train);
36
      for i = 1:N_train
37
           y_{train}(i) = sin(x_{train}(i)) + normrnd(0, 0.1);
38
      end
39
40
      %% Test data (N_test, x_test, y_test, y_gtruth)
41
      N_{\text{test}} = 1000;
42
      x_test = linspace(0, 2*pi, N_test);
43
      y_gtruth = sin(x_test); % ground truth
      for i = 1:N_{test}
44
45
           y_{test}(i) = y_{gtruth}(i) + normrnd(0, 0.1);
46
      end
47
  end
48
49 | if(plot_specific_MLP_training)
```

```
50
       %% MLP structure
51
       trainFcn = 'trainlm';
       hiddenSizes = 4;
52
53
      net = feedforwardnet (hiddenSizes, trainFcn);
54
       %% MLP training
       [net, tr] = train(net, x_train, y_train);
55
       %% MLP testing
56
       % Test error
57
58
      MLP_test = net(x_test);
59
       perf_test = perform(net,y_test, MLP_test);
60
       % Train error
61
      MLP_train = net(x_train);
62
      perf_train = perform(net,y_train,MLP_train);
63
      % Ground truth error
      perf_gtruth = perform(net, y_gtruth, MLP_test);
64
65
66
67
       %% Plot data
68
       % Plot training data
      plot(x_train, y_train, 'b.', 'DisplayName', "training data");
69
70
      hold on;
71
       % Plot test data
72
       s1 = scatter(x_test, y_test, 5, 'DisplayName', "test data", ...
73
                   'MarkerFaceColor', 'g', 'MarkerEdgeColor', 'g');
74
       alpha(s1,.1)
75
      hold on;
76
       % Plot truth data
      plot(x_test, y_gtruth, 'r-', 'DisplayName', "Sin(x)");
77
78
      hold on;
79
      % Plot MLP output for test data
      plot(x_test, MLP_test, 'k-', 'DisplayName', "MLP output");
80
81
      title("MLP training");
82
      my_subtitle = sprintf("test error: %.4f, train error: %.4f, gtruth
         error: %.4f", ...
83
                              perf_test, perf_train, perf_gtruth);
84
       subtitle(my_subtitle);
       xlabel("x");
85
86
       ylabel("y");
       legend("training data", "test data", "Sin(x)", "MLP output");
87
       figure_name = sprintf("test_error_%.3q_train_error_%.3
88
         g_gtruth_error_{\%}.3g.png", \dots
89
                              perf_test, perf_train, perf_gtruth);
90
       saveas(gcf, figure_name);
91
      hold off;
92
  end
94
  % 2. Net structure
96 | folder_name = "net_structure";
97 | if ~exist(folder_name, 'dir')
      mkdir(folder_name);
98
99 | end
```

```
100
101
    generate_data_2 = false; %%%%% <- change here as needed! %%%%%
102
103
    if(generate_data_2)
104
        %% Training data (N_train, x_train, y_train)
105
        N_{train} = 50;
106
        x_train = linspace(0, 2*pi, N_train);
107
        for i = 1:N_train
108
             y_train(i) = sin(x_train(i)) + normrnd(0, 0.1);
109
        end
110
111
        %% Test data (N_test, x_test, y_test, y_gtruth)
112
        N_{\text{test}} = 1000;
113
        x_test = linspace(0, 2*pi, N_test);
114
        y_gtruth = sin(x_test); % ground truth
115
        for i = 1:N_test
116
             y_{test}(i) = y_{gtruth}(i) + normrnd(0, 0.1);
117
        end
118
    end
119
120
    test_net_structure = false; %%%%% <- change here as needed! %%%%%
121
    neurons = 1:50;
    if (test_net_structure)
122
123
        for i = 1:numel(neurons)
124
            fprintf("Training with %d neurons in the hidden layer\n",
               neurons(i));
125
            trainFcn = 'trainlm';
126
            net = feedforwardnet (neurons(i), trainFcn);
127
            net.trainParam.epochs = 1000;
128
129
            for j = 1:5
130
                 [net, tr] = train(net, x_train, y_train);
131
                 % Test error
132
                MLP_test = net(x_test);
133
                 error_t(j) = mean((y_test-MLP_test).^2);
134
                 % per_error_t = perform(net, y_test, MLP_test);
135
                 % Train error
                MLP_train = net(x_train);
136
137
                 error_tr(j) = mean((y_train-MLP_train).^2);
138
                 % per_error_tr = perform(net, y_train, MLP_train);
139
                 % Ground truth error
140
                 error_gt(j) = mean((y_gtruth-MLP_test).^2);
141
                 % per_error_gt = perform(net, y_gtruth, MLP_test);
142
                 % fprintf(['Error_t: %f, Percent Error_t: %f, Error_tr: %f,
143
                 %
                       'Percent Error_tr: %f, Error_gt: %f, Percent Error_gt:
                     %f \setminus n' ], \ldots
                       error_t(j), per_error_t, error_tr(j), per_error_tr,
144
145
                       error_gt(j), per_error_gt);
146
            end
147
            test_error(i) = mean(error_t);
```

```
148
            train_error(i) = mean(error_tr);
            gtruth_error(i) = mean(error_gt);
149
150
            % Plot training data
            plot(x_train, y_train, 'b.', 'DisplayName', "training data");
151
152
            hold on;
            % Plot test data
153
154
            s1 = scatter(x_test, y_test, 5, 'DisplayName', "test data", ...
                         'MarkerFaceColor', 'g', 'MarkerEdgeColor', 'g');
155
156
            alpha(s1,.1)
157
            hold on;
158
            % Plot truth data
159
            plot(x_test, y_gtruth, 'r-', 'DisplayName', "Sin(x)");
160
161
            % Plot MLP output for test data
            plot(x_test, MLP_test, 'k-', 'DisplayName', "MLP output");
162
            my_title = sprintf("%d neurons", neurons(i));
163
164
            title(my_title);
165
            my_subtitle = sprintf("test error: %.4f, train error: %.4f,
               gtruth error: %.4f", ...
                                   test_error(i), train_error(i),
166
                                     gtruth_error(i));
            subtitle(my_subtitle);
167
            xlabel("x");
168
169
            ylabel("y");
170
            legend("training data", "test data", "Sin(x)", "MLP output");
171
            hold off;
            figure_name = sprintf("/%d_neurons_in_MLP.png", neurons(i));
172
            saveas(gcf, strcat(folder_name, figure_name));
173
174
            fprintf("test error: %.4f, train error: %.4f, gtruth error: %.4f
               \backslash n'', ...
175
                    test_error(i), train_error(i), gtruth_error(i));
176
            177
        end
178
        % Plot errors
        plot(neurons, test_error, 'g-', 'LineWidth', 2, 'DisplayName', 'Test
179
           Error');
180
        hold on;
        plot(neurons, train_error, 'b-', 'LineWidth', 2, 'DisplayName', '
181
          Train Error');
        plot(neurons, gtruth_error, 'r-', 'LineWidth', 2, 'DisplayName', '
182
          Ground Truth Error');
183
184
        % Title and labels
185
        title('Errors vs. Number of Neurons in Hidden Layer');
        xlabel('Number of Neurons');
186
187
        ylabel('Error');
        legend('Location', 'best');
188
189
        % Adjust figure
190
191
        grid on;
192
        figure_name = sprintf("/error_plot.png");
```

saveas(gcf, strcat(folder_name, figure_name));

193

```
194 | end
195
196
197
   % 3. Number of samples
198
   199
   folder_name = "samples_number";
200
201 | if ~exist(folder_name, 'dir')
202
       mkdir(folder_name);
203
   end
204
205
   test_samples_number = false; %%%%% <- change here as needed! %%%%%
206
   if (test_samples_number)
207
208
       \% Test data (N_test, x_test, y_test, y_gtruth) (only once)
209
       N_{\text{test}} = 1000;
210
       x_test = linspace(0, 2*pi, N_test);
211
       y_gtruth = sin(x_test); % ground truth
212
       for i = 1:N_test
213
             y_{test}(i) = y_{gtruth}(i) + normrnd(0, 0.1);
214
       end
215
216
       %% Net structure
       trainFcn = 'trainlm';
217
218
       net = feedforwardnet (5, trainFcn);
219
       net.trainParam.epochs = 50;
220
       net.trainParam.min_grad = 1e-10;
221
       net.trainParam.max_fail = 50;
222
       net.trainParam.goal = 0;
223
       net.trainParam.showWindow = false;
224
225
       data_number = 5:5:100;
226
       for i = 1:numel(data_number)
227
           %% Training data (N_train, x_train, y_train)
228
           N_train = data_number(i);
229
            disp(N_train)
230
           x_train = linspace(0, 2*pi, N_train);
231
           for k = 1:N_train
232
                 y_{train}(k) = sin(x_{train}(k)) + normrnd(0, 0.1);
233
            end
234
            fprintf("Training with %d samples\n", data_number(i));
235
236
237
            for j = 1:5
238
                [net, tr] = train(net, x_train, y_train);
239
                % Test error
240
               MLP_test = net(x_test);
241
                error_t(j) = mean((y_test - MLP_test).^2);
242
                % Train error
243
               MLP_train = net(x_train);
244
                error_tr(j) = mean((y_train - MLP_train).^2);
```

% Ground truth error

245

```
246
                error_gt(j) = mean((y_gtruth - MLP_test).^2);
247
            end
248
249
            test_error(i) = mean(error_t);
250
            train_error(i) = mean(error_tr);
            gtruth_error(i) = mean(error_gt);
251
252
            % Plot training data
253
            plot(x_train, y_train, 'b.', 'DisplayName', "training data");
254
            hold on;
255
            % Plot test data
            s1 = scatter(x_test, y_test, 5, 'DisplayName', "test data", ...
256
                          'MarkerFaceColor', 'g', 'MarkerEdgeColor', 'g');
257
258
            alpha(s1,.1)
259
            hold on;
260
            % Plot truth data
            plot(x_test, y_gtruth, 'r-', 'DisplayName', "Sin(x)");
261
262
            hold on;
263
            % Plot MLP output for test data
264
            plot(x_test, MLP_test, 'k-', 'DisplayName', "MLP output");
            my_title = sprintf("%d samples", data_number(i));
265
266
            title(my_title);
267
            my_subtitle = sprintf("test error: %.4f, train error: %.4f,
               qtruth error: %.4f", ...
268
                                   test_error(i), train_error(i),
                                      gtruth_error(i));
269
            subtitle(my_subtitle);
270
            xlabel("x");
271
            ylabel("y");
272
            legend("training data", "test data", "Sin(x)", "MLP output");
273
274
            figure_name = sprintf("/%d_samples_in_MLP.png", data_number(i));
275
            saveas(gcf, strcat(folder_name, figure_name));
276
            fprintf("test error: %.4f, train error: %.4f, gtruth error: %.4f
               \backslash n'', ...
277
                    test_error(i), train_error(i), gtruth_error(i));
278
            disp("*************;);
279
        end
280
        % Plot errors
281
        plot(data_number, test_error, 'g-', 'LineWidth', 2, 'DisplayName', '
           Test Error');
282
        hold on;
        plot(data_number, train_error, 'b-', 'LineWidth', 2, 'DisplayName',
283
           'Train Error');
        plot(data_number, gtruth_error, 'r-', 'LineWidth', 2, 'DisplayName',
284
            'Ground Truth Error');
285
286
        % Title and labels
287
        title('Errors vs. Number of Samples in the Training Set');
288
        xlabel('Number of Training Samples');
289
        ylabel('Error');
290
        legend('Location', 'best');
```

291

```
292
       % Adjust figure
293
       grid on;
294
       figure_name = sprintf("/error_plot.png");
295
       saveas(gcf, strcat(folder_name, figure_name));
296
   end
297
298
300 | % 4. Initial Values
301
   302 | folder_name = "initial_values";
303 | if ~exist(folder_name, 'dir')
304
       mkdir(folder_name);
305
   end
306
307
   test_initial_values = true; %%%%% <- change here as needed! %%%%%
308
   if (test_initial_values)
309
       %% Training data (N_train, x_train, y_train)
       N_{train} = 50;
310
311
       disp(N_train)
312
       x_train = linspace(0, 2*pi, N_train);
313
       for i = 1:N_train
314
            y_{train}(i) = sin(x_{train}(i)) + normrnd(0, 0.1);
315
       end
316
       \% Test data (N_test, x_test, y_test, y_gtruth) (only once)
317
       N_{\text{test}} = 1000;
318
       x_test = linspace(0, 2*pi, N_test);
319
       y_gtruth = sin(x_test); % ground truth
320
       for i = 1:N_{test}
321
            y_{test}(i) = y_{gtruth}(i) + normrnd(0, 0.1);
322
       end
323
324
       %% Net structure
325
       trainFcn = 'trainlm';
326
       net = feedforwardnet (5, trainFcn);
327
       net.trainParam.epochs = 50;
328
       net.trainParam.min_grad = 1e-10;
329
       net.trainParam.max_fail = 50;
330
       net.trainParam.goal = 0;
331
       net.trainParam.showWindow = false;
332
       initial_values = 1:100;
333
       for i = 1:numel(initial_values)
334
            fprintf("Training in the %d iteration\n", initial_values(i));
335
            [net, tr] = train(net, x_train, y_train);
           % Test error
336
337
           MLP_test = net(x_test);
338
           test_error(i) = mean((y_test - MLP_test).^2);
339
           % Train error
340
           MLP_train = net(x_train);
           train_error(i) = mean((y_train - MLP_train).^2);
341
342
           % Ground truth error
343
           gtruth_error(i) = mean((y_gtruth - MLP_test).^2);
```

```
344
345
            % Plot training data
            plot(x_train, y_train, 'b.', 'DisplayName', "training data");
346
347
            hold on:
348
            % Plot test data
            s1 = scatter(x_test, y_test, 5, 'DisplayName', "test data", ...
349
350
                         'MarkerFaceColor', 'g', 'MarkerEdgeColor', 'g');
351
            alpha(s1,.1)
352
            hold on;
353
            % Plot truth data
354
            plot(x_test, y_gtruth, 'r-', 'DisplayName', "Sin(x)");
355
            hold on;
356
            % Plot MLP output for test data
357
            plot(x_test, MLP_test, 'k-', 'DisplayName', "MLP output");
            my_title = sprintf("Training number %d", initial_values(i));
358
359
            title(my_title);
            my_subtitle = sprintf("test error: %.4f, train error: %.4f,
360
               gtruth error: %.4f", ...
361
                                  test_error(i), train_error(i),
                                     gtruth_error(i));
362
            subtitle(my_subtitle);
            xlabel("x");
363
364
            ylabel("y");
365
            legend("training data", "test data", "Sin(x)", "MLP output");
366
367
            figure_name = sprintf("/%d_initial_values_in_MLP.png",
               initial_values(i));
368
            % saveas(qcf, strcat(folder_name, figure_name));
            fprintf("test error: %.4f, train error: %.4f, gtruth error: %.4f
369
               \backslash n'', ...
370
                    test_error(i), train_error(i), gtruth_error(i));
371
            372
        end
373
        % Plot errors
        plot(initial_values, test_error, 'g-', 'LineWidth', 2, 'DisplayName'
374
           , 'Test Error');
375
        hold on;
        plot(initial_values, train_error, 'b-', 'LineWidth', 2, 'DisplayName
           ', 'Train Error');
        plot(initial_values, gtruth_error, 'r-', 'LineWidth', 2, '
377
          DisplayName', 'Ground Truth Error');
378
        % Title and labels
379
        title('Errors vs. Initial values sets');
380
        xlabel('Initial values sets');
381
        ylabel('Error');
        legend('Location', 'best');
382
383
        % Adjust figure
384
        grid on;
        figure_name = sprintf("/error_initial_values.png");
385
386
        saveas(gcf, strcat(folder_name, figure_name));
```

387

end

The need has arisen to unify the figures generated with Matlab in a programmatic way, for which the following code has been implemented in Python.

Listing 1: Python code for image grouping

```
import matplotlib.pyplot as plt
1
2
   import matplotlib.image as mpimg
3
   figure_directory = "."
4
   numbers_to_select = [1, 3, 5, 10, 20, 30, 40, 50]
5
  fig, axes = plt.subplots(4, 2, figsize=(20, 10))
6
   plt.subplots_adjust(wspace=-1, hspace=0.01)
7
   axes = axes.flatten()
8
9
   for i, num in enumerate(numbers_to_select):
10
       figure_name = f"{figure_directory}/{num}_neurons_in_MLP.png"
11
       img = mpimg.imread(figure_name)
12
       axes[i].imshow(img)
13
       axes[i].axis('off')
14
15
16
   for j in range(len(numbers_to_select), len(axes)):
17
       fig.delaxes(axes[j])
18
19
   plt.tight_layout()
   plt.savefig("selected_figures_grid.png")
20
21
   plt.show()
```