# Using Python and Scikit-learn to Construct Artificial Neural Networks

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### 1 Outline

In this text we explain how to construct an artificial neural network that given known data of chemical compounds and their properties, will predict the property of an unknown chemical compound. For this purpose, chemical compounds are represented as *feature vectors* that are obtained from the structure of the compounds. We will describe a program that given pairs of feature vectors of chemical compounds and values for some chemical property, constructs an artificial neural network, and explain how to get the parameters (weights and biases) of the trained neural network.

We use the scikit-learn library for machine learning in the Python programming language. Please check further details at the following web-page: https://scikit-learn.org/stable/

Note that this text is accompanied by the following three files

### • scikit\_chemgraph\_learning.py

A program written in Python that given a dataset of pairs of feature vectors and observed values of chemical properties, constructs an artificial neural network using 5-fold cross-validation. The weights and biases of the trained neural network that achieved the highest coefficient of determination ( $\mathbb{R}^2$ ) score over the test data are stored as output files. Further details are given in Section 4.

### • ha\_fv4\_plus.csv

Computed feature vectors of chemical compounds in the PubChem database with known values for the property *heat of atomization*.

### • ha\_target\_data.csv

A comma-separated-value file containing observed values of chemical property heat of atomization of compounds in the PubChem chemical database.

Section 3 contains further details on the file format, and Section 5 gives the results of computational experiments using the dataset from the above two files.

The remainder of this text is organized as follows. Section 2 gives basic terminology used throughout the text. Section 3 explains the format of the input and output of the program. In particular, an actual example of program input and output is used. Section 4 gives further details on the source code of the program. Section 5 gives the results of an actual computational experiment.

### 2 Terminology

In this section we explain some of the terminology used throughout the text.

### • Feature vector

A vector of numerical values describing a chemical compound, such as the number of atoms of each element type, or calculated based on the topology of the graph representation of a chemical compound, such as the graph's diameter.

### • Neural network

Artificial neural networks, or simply neural networks, are one of the most well-established methods in machine learning. They are used to predict a value based on an input vector. In this text, the input to neural networks is a feature vector of a chemical compound, and the output is a predicted value for a certain chemical property.

### • Input layer, hidden layers, output layer

We assume the multi-layer perceptron model for artificial neural networks. In this model, neural networks comprise several *layers*. The first of these layers is the input layer, taking numerical data, in out case, from a feature vector, and therefore the input layer has the same number of nodes as elements in the feature vector. Next, these numeric values are propagated through the networks *hidden* layers, where the calculation of one layer is used as an input to the next. At last, the output layer gives the predicted value based on the input vector.

### • Weight

In a neural network nodes are interconnected by edges, and each edge is assigned a numerical value, or *weight*. The propagation of the values from the input layer to the output layer involves calculation based on these weights.

### • Bias

Each node in the hidden layers of a neural network is assigned a numerical value, called a bias, which together with the weights is used in calculating an output value based on the input vector.

The neural network "learns" by calculating a set of weights and biases based on given pairs of input vectors and target values.

### • Activation function

An activation function is assigned to each node of a neural network, and is used in calculating an output value from a given vector of input values. In particular, the output value of each node is the value of the activation function given as input a linear combination of the outputs of the nodes from the previous layer, weighted by the corresponding edge weights.

### 3 Program Input and Output

This section gives details on the input and output format of the Python program. Section 3.1 gives an explanation of the input to the program using an actual example with the chemical property heat of atomization. Section 3.2 gives details of the input data format. Section 3.3 gives an explanation of the actual output produced from the input data. Section 3.4 explains the format of the output data.

### 3.1 Program Input

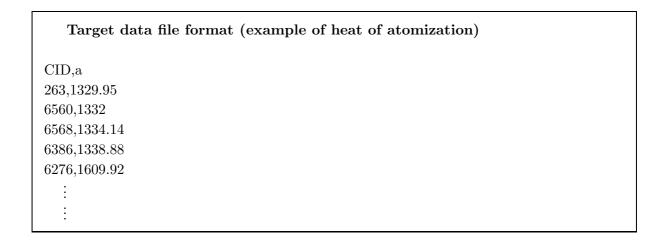
As input the Python program takes two sets of data. One is a file containing the feature vectors of a set of chemical compounds, and the other is a file containing the numerical values of some observed chemical property over the same set of compounds. The program constructs and trains a neural network given these two files.

### 3.2 Input data format

This section describes the format of the two files that are input to the program as explained in Section 3.1.

First, we explain the format of the file giving the feature vectors. It is a comma-separated-value (csv) file, in plain text format. The first row gives the names of each descriptor of the feature vector, whose first entry is the a compound identification number (CID) of the chemical compound, and is not used in learning or prediction. Following, from the second row onward, the feature vector of several chemical compounds are given, each value separated by a comma, and each feature vector in one line.

Next we explain the structure of a csv file that contains the target values of a chemical property. The first line simply gives the table heading as "CID,a", where CID is a compound's ID number, and "a" denotes the target value. The following lines are the ID and target values of chemical compounds, given in the same order as in the feature vector csv file.



### 3.3 Program output

Figure 1 gives an example of a trained neural network, with calculated edge weights and node biases. The final output of the program is a file containing the weights and biases of a trained neural network.

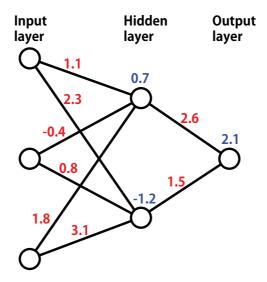


Figure 1: An example of a trained artificial neural network. The red numbers next to edges give the weights, and blue numbers next to nodes give the biases.

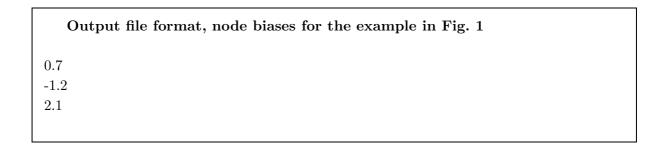
### 3.4 Output format

The edge weights and node biases resulting from a trained neural network from the program are written in two respective output files.

The first line of the output file with edge weight data gives the architecture of the artificial neural network, that is, the number of nodes in the input layer, then the numbers of nodes in each hidden layer, and finally, the number of nodes in the output layer. From the second line onward follow the values of the edge weights. Each row gives the values of the edges going out of a single node.

# Output file format, edge weights for the example in Fig. 1 3 2 1 1.1 2.3 -0.4 0.8 1.8 3.1 2.6 1.5

The file containing the node biases contains one node bias value per line. Not that nodes in the input layer do not have bias values.



### 4 Explanation of the program

This section explains a program implemented in the Python programming language that reads input files with feature vector values and target data as explained in Sections 3.1 and 3.2, trains an artificial neural network using five-fold cross-validation, and produces output files containing the edge weights and node biases of the neural network that achieves the highest coefficient of determination ( $\mathbb{R}^2$ ) test score over the five cross-validation tests. The format of the output files is as described in Sections 3.3 and 3.4.

The source code of the program is given in the file scikit\_chemgraph\_learning.py, and given completely as code sample 2.

```
scikit_chemgraph_learning.py
  This file implements functions that given a file with
  descriptor values of chemical compounds and a file with target values,
  performs 5-fold learning using an artificial neural network (MLP regressor)
  and stores the weights and biases of the training iteration that achieved
10 the highest R^2 test score over the 5 trials.
11
12 Command line arguments include
  - filename with a list of descriptors
13
  - filename with a list of target values
14
  - filename for the output weights and biases
  - network architecture, as a list of hidden layer sizes
16
^{18} The program will output on the terminal the R^2 and MAE scores, and
  time taken for training for each
19
  trial in the 5-fold cross-validation,
  and the averages over the 5 trials at the end.
21
22
23
24 import numpy as np
25 import pandas as pd
  from sklearn.model_selection import KFold
  from sklearn.neural_network import MLPRegressor
28 from sklearn.metrics import mean_absolute_error
29 import time
30 import sys
31
  def write_weights_biases (reg, filename):
32
33
      This function will write to disk 2 files, called
34
          "filename_weights.txt" and
35
          "filename_biases.txt"
36
      containing the weights and biases
37
      of a trained artificial neural network reg given as an argument
38
39
      # initialize separate filenames
40
      weights_filename = filename + "_weights.txt"
41
      biases_filename = filename + "_biases.txt"
42
43
      # Get the weights and biases from the trained MLP regressor
44
      weights = reg.coefs_
45
      biases = reg.intercepts_
```

```
num_features = weights [0]. shape [0]
47
48
       # Write the weights to file weights_filename
49
       with open(weights_filename, 'w') as f:
50
           f.write(str(num\_features) + ', ')
51
           for i in range(len(reg.hidden_layer_sizes)):
52
                f.write(str(reg.hidden_layer_sizes[i]) + '')
53
           f.write('1\n')
54
           for item in weights:
55
                for i in range (item.shape [0]):
56
                    for j in range(item.shape[1]):
57
                        if abs(item[i][j]) > 10**(-308):
58
                            f.write(str(item[i][j]) + ',')
59
60
                            f.write(',0')
61
                    f.write('\n')
62
63
       # Write the biases to a file biases_filename
64
       with open(biases_filename, 'w') as f:
65
           for item in biases:
66
                for i in range(item.shape[0]):
67
                    f.write(str(item[i])+ '\n')
68
69
70
   def train_ANN(descriptors_filename, target_values_filename, architecture):
71
72
73
       Given filenames of a file containing a list of descriptors
       and a file containing target values, and a tuple of integers
74
       giving the number of nodes in hidden layers of an ANN,
75
       perform 5-fold cross-validation learning by using the
76
       descriptors and target values with an ANN of the given architectire,
77
       and return the trained ANN (MLP regressor) that achieved the highest
78
       R^2 test score over the test data.
79
80
81
       # read the training and target data
82
       fv = pd.read_csv(descriptors_filename)
83
       value = pd.read_csv(target_values_filename)
84
85
86
       # prepare target, train, test arrays
87
       target = np.array(value['a'])
88
       x = fv.values[:,1:]
89
       y = target
90
91
       print('n range = [{},{}]'.format(fv['n'].min(),fv['n'].max()))
92
       print('a range = [\{\}, \{\}]'.format(value['a'].min(), value['a'].max()))
93
94
       numdata = x.shape[0]
95
96
       numfeature = x.shape[1]
97
       print('#instances = {}'.format(numdata))
       print('#features = {}'.format(numfeature))
98
99
       # Initialize an artificial neural network - MLP regressor
100
       reg = MLPRegressor(activation='relu', solver='adam',
101
                           alpha=1e-5, hidden_layer_sizes=architecture,
102
                           random_state=1, max_iter=100000000)
103
104
```

```
score_R2 = np.array([])
105
       score_MAE = np.array([])
106
       time_train = np.array([])
107
108
       # Separate the data randomly for cross-validation
109
       kf = KFold(n_splits=5, shuffle=True, random_state=21)
110
111
       for train, test in kf.split(x):
112
            fold += 1
113
            x_{train}, x_{test}, y_{train}, y_{test} = x[train], x[test], y[train], y[test]
114
            print('\nD{}: train {}, test {}'.format(fold,
115
                  x_{train.shape}[0], x_{test.shape}[0])
116
117
            start = time.time()
118
            reg.fit(x_train, y_train)
119
            end = time.time()
120
            timetemp = end-start
121
122
            print('training time: {}'.format(timetemp))
123
            time_train = np.append(time_train, timetemp)
124
125
126
            pred = reg.predict(x)
            pred_train = reg.predict(x_train)
127
            pred_test = reg.predict(x_test)
128
129
           # calculate the prediction score (R^2)
130
            R2train = reg.score(x_train, y_train)
131
            R2test = reg.score(x_test, y_test)
132
            R2all = reg.score(x,y)
133
            print ('R2 score train = {}'.format (R2train))
134
            print('R2 score test = {}'.format(R2test))
135
            print('R2 score all = {})'.format(R2all))
136
            temp = np.array([R2train, R2test, R2all]).reshape(1,3)
137
            score_R2 = np.append(score_R2, temp)
138
139
140
           # check the test R2 score and store the regressor with the highest one
            if (fold == 1):
141
                best\_regressor = reg
142
                best_R2\_score = R2test
143
144
            else:
                if (R2test > best_R2_score):
145
                     best\_regressor = reg
146
                     best_R2_score = R2test
147
148
       score_R2 = score_R2.reshape(5,3)
149
       avg_time = np.mean(time_train)
150
       print('\nAverage time = {}'.format(avg_time))
151
       avg\_testR2 = np.mean(score\_R2, 0)[1]
152
       print('Average R2 test score = {}'.format(avg_testR2))
153
154
       return best_regressor
155
156
157
   def main(argv):
158
       if (len(argv) < 5):
159
            print("""
160
                  Please supply at least 4 command line arguments:
161
                      - Descriptors as training data
162
```

```
- Target values as training data
163
                      - Filename for the output weights/biases files
164
                      - number of nodes in at least one hidden layer
165
166
                  The program will now terminate.""")
167
           sys.exit()
168
       # else:
169
       # Parse the command line arguments
170
       descriptors_filename = argv[1]
171
       target_values_filename = argv[2]
172
       output_filename = argv [3]
173
       architecture = tuple(int(a) for a in argv[4:])
174
175
       # Perform 5-fold validation with the given training data
176
       # and return the regressor that achieves highest R^2 test score
177
       best_regressor = train_ANN(descriptors_filename,
178
                                                      target_values_filename,
179
180
                                                      architecture)
181
       # Write the weights and biases of the regressor to files
182
       write_weights_biases(best_regressor, output_filename)
183
184
185
  main(sys.argv)
186
```

Code sample 2: Source code file scikit\_chemgraph\_learning.py.

The program initializes an artificial neural network in line 101, using the rectified linear unit function (relu) as as activation function. Please check further details on the hyper-parameters for artificial neural networks at the official scikit web-page:

https://scikit-learn.org/

### 5 Program execution and a computational example

In this section we explain how to execute the program by using a real example. As training data we use target data for the property heat of atomization, and feature vectors for compounds obtained from the PubChem database.

### 5.1 Executing the program

Please make sure that you have Python 3 enabled environment. It is recommended to use a distribution such as Anaconda which contains many of the necessary accompanying packages. https://www.anaconda.com/distribution/

We assume that the program source code scikit\_chemgraph\_learning.py and the sample input files ha\_fv4\_plus.csv and ha\_target\_data.csv are located in the same folder. As an example, we will construct artificial neural networks with one hidden layer that has ten nodes. The edge weights and node biases of the resulting artificial neural network will be written in files ANN\_weights.txt and ANN\_biases.txt, respectively.

To execute the code, in a Python-enabled terminal type:

python3 scikit\_chemgraph\_learning.py ha\_fv4\_plus.csv ha\_target\_data.csv ANN 10

Two new files should appear in the folder, ANN\_weights.txt and ANN\_biases.txt, containing the edge weight values and node bias values, respectively. During the computation process, the program will print on the terminal the status of each cross-validation trial, including the number of training data samples, the time it took to train the artificial network, and the  $\mathbb{R}^2$  score.

### 5.2 Computational example

Here we give the results obtained by running the program with the sample input files ha\_fv4\_plus.csv and ha\_target\_data.csv.

First we give the contents of the output file ANN\_weights.txt containing the edge weights of a trained artificial neural network. The format of the file is as described in Section 3.4.

### Actual contents of file ANN\_weights.txt

22 10 1

- $-1.1238112931499422e-84 \qquad 3.0170452635900533 \qquad -1.6241043622384792e-73 \qquad -3.6018735325629394 \quad -8.391988020519093e-77 \quad 2.3580716556323953 \quad -0.026736972121934502$
- $2.575726292584817 \ -2.063731712717064 \\ e-06 \ 4.597303330113335$
- $-9.344488035266295 \\ e-85 \quad 1.497290480000622 \quad -3.036274715861717 \\ e-78 \quad 1.8156784526785696$
- -0.011238853071123057 -0.7443192517629607

- $-2.1917950390948578 \\ e-06\ \ 4.771137374239634$
- $-1.1581526717811436e-75 \\ -1.329707686671036 \\ 2.0796776718616044e-74 \\ 6.237593937811961$
- $4.1273697169652248e-81 \ \ -1.4062510180009142 \ \ -0.026704728711823528 \ \ -0.925294417115918$

```
-6.740518660092261e-74 -5.540003285685092
9.543615511411743 \\ e-74 \quad -1.1589876575808225 \quad -2.6364157708348452 \\ e-80 \quad 3.187561980333966
-8.943738918434615 \mathrm{e}{-76} \ -1.4524340822049775 \ 0.051782929796906886 \ -1.5653228064901121
-1.6249155288107357e-80 -3.634647585954396
-6.39468464326263 - 74 \quad 3.0629683725323584 \quad -1.9774305352016877 - 78 \quad -3.7172015955219266
-3.7919200519635786e - 88 \quad 2.4044443070857207 \quad -0.02401369830407232 \quad 2.4832637050782376
-0.00022794649906475431 4.66431434861339
-9.377192677863584 e - 76 \quad 3.004803749408999 \quad 4.902837933366572 e - 81 \quad -2.5013050438170104
-1.4036823325175825 \\ e-74 \\ 2.998787164164196 \\ -0.026861635340365342 \\ 2.981392380037406
1.0661485018096706e-74 2.3304790128834076
1.2701574125840252e-75
                                                      2.7221295483347125
                                                                                                     -1.2703118087438868e-76
2.9194172521756747 \quad -5.544716411580953 \\ \text{e-}84 \quad 2.630411509774059 \quad -0.015116670855903482
2.7865193029822377 \ -8.887535520464753 e - 07 \ 4.436851466042201
4.351938047328309 \\ e-76 \quad 1.1180131069815742 \quad 1.9824013505096927 \\ e-79 \quad 0.9464827643663908
-5.2330770435602964 \\ e-80 \quad 1.2998557027642679 \quad -0.0271136889312177 \quad 1.3721987711511763
5.654281723895746e-82 -1.1521340765967187
-4.832882183847715 \\ e-76 \\ -0.984636501818488 \\ -5.8925978392141506 \\ e-86 \\ 3.0049263389599625
-2.3626537886806268e-84 \ -1.6350496714029827 \ 0.05142288752338433 \ -1.3227793558667296
-1.422705004455725e-73 -3.6206407833583314
-1.1423162173298355 \\ e-81 \ 2.5902312579960958 \ 5.014920153233757 \\ e-76 \ -3.4344337828410194
1.6638832030159978e-75 \quad 2.5636947094464215 \quad -0.03842125857490203 \quad 2.8294384537406594
-3.378684191548278e-07 4.509451556355702
-1.9791643476720933 \\ e-77 \quad 2.575887805003329 \quad 5.789281131361252 \\ e-75 \quad -2.7281627756446336 \\ e-75 \quad -2.72816277564663 \\ e-75 \quad -2.72816277564 \\ e-75 \quad -2.7281627756 \\ e-75 \quad -2.728162756 \\ e-75 \quad -2.72816756 \\ e-75 \quad -2.728162756 \\ e-75 \quad -2.72816756 \\ e-75 \quad -2.7281756 \\ e-75 \quad -2.7281
-6.220513272189593 \mathrm{e}{-75} \quad 2.998889390482911 \quad -0.022617802565271246 \quad 3.141560745624169
1.414233611426763e-19 4.20142249839257
-6.236323873029463\mathrm{e}\text{-}74\ \ 2.5328911726682506\ \ -4.1242465272786166\mathrm{e}\text{-}74\ \ -4.325696725950309
1.2224358229010616 e-76 \\ 2.8538143450705977 \\ -0.027122334983233323 \\ 3.113071693728851 \\
-2.904059652886194e-765.198706814683436
1.420883684820555 e-84 \quad 4.419013439859128 \quad 1.6389532350787483 e-85 \quad -4.979526814267058
4.1052218408326557e-78 \quad 3.652082980531675 \quad -0.024619557800014336 \quad 3.7853797365655724
-3.116805665467011e-12\ 5.524734571674539
1.0539941002876462e-85
                                                    -1.484006161426568e-76
                                                                                                         -8.481259995666099e-75
                                                   -1.840734810369072e-74
3.385627263079466e-76
                                                                                                        -7.126209692448427e-76
8.430081625400892e-79
                                                   1.7094068447294007e-80
                                                                                                        1.4534199593339358e-85
8.909642175302103e-74
-4.579216934717519e-75
                                                                                                          3.096517969737067e-85
                                                     3.3160819289390773e-74
3.252893330112976e-78
                                                   -1.6131377874071942e-79
                                                                                                          1.264042447674757e-79
5.178853335658389e-78
                                                           9.79532619082707e-85
                                                                                                                     3.7975705026371116e-74
5.864667199962804e-77
-3.527077784355358e-79 1.0055144424417832 2.2306081105728293e-83 1.3622446947832159
-4.785545338835612\mathrm{e}{-77} \quad 0.5400841311524589 \quad -0.03624633129780699 \quad 0.9578106090827272
7.644113549863133e-84 -1.1524755436280696
-2.1846619808211293e-81
                                                      9.430959196585263e-74
                                                                                                          8.536075853537646e-85
                                                           6.398633625096473e-86
                                                                                                                     1.3910501842751384e-79
2.2139284118700775e-83
8.538704976080743e-82 -7.228543198210997e-80
                                                                                                         -6.114976978023107e-75
```

```
4.7877245965779975e-83
4.716163509148316e - 83 \quad 1.3567662696569605 \quad 2.2217242689278444e - 79 \quad 0.3595889984417734
-9.709418766252208e - 80 \quad 1.7984676174734713 \quad -0.026019205526194706 \quad 1.6645822669313806
-2.7524293292069654e-41\ 0.4640785972370295
-8.022393348473078 \\ e-80 \\ 2.388617171015578 \\ 7.2218184954467 \\ e-80 \\ -2.938485874134715
1.6022431880262786e-75 3.0259704996411654 -0.03858141275439007 2.420664143890053
-9.293345821386595e-11 4.428153114188145
1.4128633719441486e-74 1.3504763123701526 2.4079461071148895e-75 2.836623998649334
-1.0226076926010233 \\ e-83 \quad 1.2329765686923553 \quad -0.02707091168288496 \quad 1.2994911562472369
-2.684035828287667e-21 -0.9459205356006979
-6.942528315035475 e-84 \quad 1.5334486738127497 \quad -1.804093649532225 e-77 \quad 1.8778133808947834
-1.6006530414671997 \\ e-76 \quad 1.083156020823177 \quad -0.04084555054335288 \quad 1.4765446070889678
-3.100280920791693e-21\ 0.11736440513790376
-3.1879771652517114e-85
1.916134889181373
2.5464128802342342e-73
-3.0910705862093906
-1.444253829353331e-87
2.0276392094212436
-0.06469567595196621
2.1390744407926197
0.002829845412690173
```

Next, we give the contents of the file ANN\_biases.txt containing the node bias values of a trained neural network. See Section 3.4 for the format of this file.

### Actual contents of file ANN\_biases.txt

-0.28042226851252594

1.5596289736806637

3.5091525125068657

-0.31956610647035755

-0.0872512930439685

 $\hbox{-}0.1344620030528743$ 

2.008407301702276

0.047331275321582

1.9639995776527803

0.27090672942420446

1.6755999282930374

0.7785606509372179

### Output of the program written on the terminal screen

```
n range = [4,11]
a range = [1100.6, 3009.57]
#instances = 115
#features = 22
D1: train 92, test 23
training time: 5.539255857467651
R2 \text{ score train} = 0.999972246284607
R2 \text{ score test} = 0.9995125971676746
R2 \text{ score all} = 0.9998742854857515
D2: train 92, test 23
training time: 5.087205410003662
R2 \text{ score train} = 0.9998472762457117
R2 \text{ score test} = 0.999827361127545
R2 \text{ score all} = 0.9998423496039506
D3: train 92, test 23
training time: 5.4368956089019775
R2 \text{ score train} = 0.9998628977117406
R2 \text{ score test} = 0.9999531906631327
R2 \text{ score all} = 0.999878508348101
D4: train 92, test 23
training time: 5.512180805206299
R2 \text{ score train} = 0.999865105990373
R2 \text{ score test} = 0.9999472183270992
R2 score all = 0.999877833093491
D5: train 92, test 23
training time: 6.058949947357178
R2 \text{ score train} = 0.9998589982852477
R2 \text{ score test} = 0.9999391731973049
R2 score all = 0.999876634586547
Average time = 5.526897525787353
Average R2 test score = 0.9998359080965512
```