

# Mex Usage

## C1 Introduction

This document explains the use of the mex files `libsdnn_train.mexw64` and `libsdnn_test.mexw64` in the `LIBSDNN/mex` folder. These mex files are written in C++ and compiled using Visual Studio 2017.

## C2 Installation

Move the both of the `libsdnn_train.mexw64` and `libsdnn_test.mexw64` into the Matlab(R) path folder. These `.mexw64` files are produced by compiling, `libsdnn_train.cpp` and `libsdnn_test.cpp` on Matlab using the `mex` command (note that these `.cpp` files can only be compiled using the Visual C++ compiler). You can find additional information on the `mex` command in the Matlab article referenced at the end of this document (Matlab 2017).

## C3 Quick Guide

1. Save the parameter files, including the selective desensitization file and/or correlation matrix file, to the current folder.
2. Use the `libsdnn_train` command to train the SDNN using training samples and produce an SDNN-model file.
3. Use the `libsdnn_test` command to estimate/recognize testing samples.

## C4 Command details

### C4-1 `libsdnn_train`

```
libsdnn_train(  
    sdn_parameter_file,  
    input_list,  
    target_list,  
    completion_condition,  
    training_result_file  
)
```

This command trains the SDNN and produces an SDNN-model file containing the parameters and synaptic weights of the SDNN.

Arguments:

- `sdn_parameter_file` (Character string)  
The name of the parameter file; please refer to **How to describe a parameter file** for further details.
- `input list` (Matrix)  
The list of training sample input vectors (see also Chapter C5).
- `target list` (Vector)  
The list of training sample target values (see also Chapter C5).
- `completion_condition` (Character string)  
The training-completion condition, which is represented in the form `string`. The setting can be one of the following strings:
  - ◆ `iteration( $n$ )`  
This tells the SDNN to repeat training procedure  $n$  times.
  - ◆ `rmse( $p,m$ )`  
This tells the SDNN to repeat the training process until the root-mean-square error is less than  $p$ . If the SDNN cannot satisfy the condition after  $m$  iterations, the training

process terminates. This completion condition can only be applied to function approximation issues.

◆ **accuracy( $a, m$ )**

This tells the SDNN to repeat the training process until the classification accuracy becomes greater than  $a$ . If the SDNN cannot satisfy this condition after  $m$  iterations, the training process terminates. This completion condition can only be applied to pattern recognition issues.

➤ **training\_result\_file** (Character string)

The name of the SDNN-model file; its extension should be .bin.

Output:

void

## C4-2 libsdnn\_test

```
libsdnn_test(
    SDNN_model_file,
    input_list
)
```

Loads the SDNN-model file and recognizes/estimates the testing samples.

Arguments:

➤ **SDNN\_model\_file** (Character string)

The name of the SDNN-model file. The SDNN-model file can be created using the libsdnn\_train command as well as other applications (static library, command line tools).

➤ **input list** (Matrix)

The list of tested sample input vectors.

Output:

A list of recognition/estimation result output vectors.

## C5 How to make an input/target list

The input list matrix  $\mathbf{I}$  and the target list vector  $\mathbf{t}$  of training/testing samples must be written in the following forms:

$$\mathbf{I} = (\mathbf{i}_1 \quad \cdots \quad \mathbf{i}_n) = \left( \begin{pmatrix} i_{11} \\ \vdots \\ i_{1m} \end{pmatrix} \quad \cdots \quad \begin{pmatrix} i_{n1} \\ \vdots \\ i_{nm} \end{pmatrix} \right),$$

$$\mathbf{t} = (t_1 \quad \cdots \quad t_n).$$

Each column of the input list matrix is assigned to an input vector of a sample. The ordering of elements in the input list matrix must match that in the target vector. Please note that numerical inputs must be normalized in the range of  $[0, 1]$  and symbolic inputs must be specified using integers starting from 0. The target vector must be specified using integers starting from 0 when pattern recognition issues are applied.

## C6 Example

Here, we demonstrate construction of an .m file using a function approximation problem (Nonaka et al. 2011) as an example. They approximated a two-variable function using an SDNN as follows:

$$f(x, y) = \begin{cases} 1 & ((x - 0.5)^2 + (y - 0.5)^2 \leq 0.04) \\ \frac{1+x}{2} \sin^2(6\pi\sqrt{xy}^2) & (\text{otherwise}) \end{cases} \quad (x, y \in [0, 1]) \quad (\text{C-1})$$

### C6-1 Making parameter files

In this demonstration, we use `parameter_file.txt`, which is saved in `LIBSDNN/mex/examples`. Please refer to the document **How to describe parameter files** for further details.

### C6-2 Preparing training/test samples

The training and testing samples are stored in `training_sample.csv` and `testing_sample.csv`, respectively. In these files, each sample is written on a single line in the form `target_value, input_1, input_2`.

The following shows an example of the source used to prepare samples:

```
x = csvread('training_sample.csv');
training_input = x(:,2:3);
training_target = x(:,1:1);
x = csvread('testing_sample.csv');
test_input = x(:,2:3);
test_target = x(:,1:1);
```

### C6-3 Training SDNN

To obtain the trained SDNN-model file, the `libsdnn_train` command is used as follows. In this example, we have transposed `training_input` and `training_target` and converted them into a suitable form following the procedure in Chapter C5 above:

```
libsdnn_train('parameter_file.txt', training_input', training_target', 'iteration(300)',
              'SDNN_model.bin');
```

### C6-4 Approximating functions

To approximate the function, use the `libsdnn_test` command as follows:

```
result = libsdnn_test('SDNN_model.bin', test_input');
```

The recognition/estimation results will be stored in `result` in the form of a row vector.

## Reference

MathWorks, “Build MEX function from C/C++ or Fortran source code,”

[https://www.mathworks.com/help/matlab/ref/mex.html?searchHighlight=mex%20build&sid=doc\\_srchttitle](https://www.mathworks.com/help/matlab/ref/mex.html?searchHighlight=mex%20build&sid=doc_srchttitle) (accessed online 2017/7/23)

K. Nonaka, F. Tanaka, and M. Morita. Empirical comparison of feedforward neural network on two-variable function approximation. *IEICE TRANSACTIONS on Information and Systems* (in Japanese), J94 (12): 2114-2125, 2011.