

A Short Instruction for nnbarrier

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1 Introduction

In our paper *Synthesizing Barrier Certificates Using Neural Networks* accepted by HSCC'20, we developed a tool named `nnbarrier` that can automatically learn a barrier certificate represented by a neural network for the safety verification of a continuous dynamical system. Here we give a short instruction to the use of `nnbarrier`, covering the system requirements, installation process, the structure of source codes, sample inputs, and user-defined inputs. We will emphasize what parts that were presented in the submitted paper will be covered in the instruction, for the purpose of repeatability evaluation. If there is any problem in using `nnbarrier`, please contact `zhaohj2016@swu.edu.cn`.

2 Installation

2.1 System Requirements

It is assumed that you have Python Version 3.x installed on your system. We have tested `nnbarrier` on Ubuntu Linux, Mac OS, and Windows (see Table 1).

2.2 Dependent Packages

It is assumed that you have the python package manager Pip installed for Python 3.x, which will facilitate the installation of dependent packages greatly.

Essentially, to run `nnbarrier` without visualization, the only two packages you need to install are Pytorch and NumPy. It seems that `numpy` will be automatically installed when installing Pytorch. Please visit <https://pytorch.org/> for the installation instructions for the popular machine learning platform Pytorch. For example, with the combination Mac+Python 3.7+Pip (without cuda GPU support), the latest stable version Pytorch 1.3 can be installed by simply run

```
pip3 install torch torchvision
```

If you would like to visualize the generated barrier function together with the considered system, i.e. the system dynamics, the domain, the initial set, and the unsafe/safe region, then some additional graphics packages are required. For visualization of 2D systems, `matplotlib` needs to be installed, and you are referred to

<https://matplotlib.org/users/installing.html> for the instructions. In the implementation of `nnbarrier`, visualization of 3D systems is supported by `Mayavi`, a 3D scientific data visualization library. Please visit <http://docs.enthought.com/mayavi/mayavi/installation.html#installing-with-pip> for the installation of `mayavi` and its dependencies (e.g. `PyQt5`). In our testing, on most platforms the visualization-required packages can be installed with the following commands easily:

```
pip install matplotlib
pip install mayavi
pip install PyQt5
```

where `pip` can be actually `pip3`. However, we do met some problems occasionally. If you failed to get this done in the end, `nnbarrier` can still be run by commenting the statements for visualization, which will be explained later.

In summary, we have tested `nnbarrier` using the following combinations

Table 1. Tested platforms and packages for `nnbarrier`

| OS | Python | Pip | Pytorch | Visualization |
|-----------------|--------|--------|---------|---------------------------|
| Ubuntu 18.04.02 | 3.6.7 | 9.0.1 | 1.2.0 | matplotlib+mayavi+PyQt5 |
| Ubuntu 18.04.02 | 3.6.9 | 19.3.1 | 1.3.1 | matplotlib+mayavi+PyQt5 |
| Windows 10 1903 | 3.7.3 | 19.3.1 | 1.3.1 | matplotlib+mayavi+PyQt5 |
| Mac OS 10.11.6 | 3.7.6 | 19.3.1 | 1.3.1 | matplotlib+mayavi+PySide2 |

2.3 Obtain the `nnbarrier` Package

Suppose that you have `Git` installed on your system. Then the `nnbarrier` package can be obtained via

```
git clone https://github.com/zhaohj2017/HSCC20-Repeatability
```

Sturcture of the Package. The cloned directory `HSCC20-Repeatability` consists of 10 Python source files and one file folder as listed below:

- `acti.py`: self-defined activation functions (i.e. *Bent-ReLU*) for neural networks
- `ann.py`: generating a multi-layer neural network model (NN for short)
- `data.py`: generating batches of training data
- `loss.py`: given a NN and a training data set, computes a loss value
- `lrates.py`: self-defined learning rate adjusting strategy
- `main.py`: the main file to run
- `opt.py`: a set of optimizers provided by `Pytorch` to train the neural network
- `plot.py`: visualization of 2D systems
- `plot3d.py`: visualization of 3D systems
- `train.py`: the training loop that iterates through batches, epochs, and restarts

- `cases`: a file folder consisting of all the problem definitions for the case studies in our paper

Inside `cases`, there are 5 sub-folders corresponding to the examples in the paper:

- `eg1.prajna_original`: the classical problem from [3], corresponding to the running example Example 1 and its continuations in our paper
- `eg2.prajna_modified`: modified version of the problem from [3], corresponding to Example 2 in our paper
- `eg3.darboux`: the *Darboux-type* barrier certificate problem from [4], corresponding to Example 3 in our paper
- `eg4.exponential`: the *exponential* barrier certificate problem from [2], corresponding to Example 4 in our paper
- `eg5.obstacle`: the aircraft obstacle avoidance problem modified from [1], corresponding to Example 5 in our paper

Each of the 5 sub-folders consists of 2 Python source files with the same names but different contents:

- `prob.py`: specify the safety verification problem of the corresponding example
- `superp.py`: specify the super-parameters for training the neural network of the corresponding problem

These are the two files that needs modification for solving user-defined problems.

Test nnbarrier. Suppose you are using Linux or Mac and located in the HSCC20-Repeatability. Execute the command

```
cp ./cases/eg1_prajna_original/*.py .
```

to copy the problem definition and parameter specification files to current directory. Then `nnbarrier` can be invoked by executing

```
python main.py
```

where `python` can actually be `python3` on your platform. If all the packages aforementioned are correctly installed, then the training process starts (see Fig. 1). Upon termination you will see a popup window illustrating the plotted barrier certificate, as presented in our paper.

3 Sample Inputs

Here we explain more about the three source files `main.py`, `prob.py`, and `superp.py` using Example 1.

```

HSCC20-Repeatability -- -bash -- 179x49
bogon:HSCC20-Repeatability zhaohj$ python3 main.py
Initialize parameters!

restart: 0 epoch: 0 batch: 0 batch_loss: 11.479664883747184 batch_gradient: 2.249706876730141 epoch_loss: 0
restart: 0 epoch: 0 batch: 1 batch_loss: 0.0 batch_gradient: 0.048395319224973796 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 2 batch_loss: 0.0 batch_gradient: 0.07644415674318973 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 3 batch_loss: 0.0 batch_gradient: 0.9696713730597358 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 4 batch_loss: 0.0 batch_gradient: 2.313834157912724 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 5 batch_loss: 0.0 batch_gradient: 0.04804878133412093 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 6 batch_loss: 0.0 batch_gradient: 2.3192165964066183 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 7 batch_loss: 0.0 batch_gradient: 0.8792931393765403 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 8 batch_loss: 0.0 batch_gradient: 2.314150034922526 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 9 batch_loss: 0.0 batch_gradient: 2.3138398617853766 epoch_loss: 11.479664883747184
restart: 0 epoch: 0 batch: 10 batch_loss: 0.0 batch_gradient: 0.0480411371684844 epoch_loss: 11.479664883747184

```

Fig. 1. The training process showing the number of restarts, epochs, batches, current gradient, and the current loss

3.1 main.py

3.2 prob.py

3.3 superp.py

3.4 User-defined inputs

```

2 import torch.nn as nn
3 import numpy as np
4 import superp
5 import prob

1 if i==0:
2     abc
3 else:
4     def

```

python3: -version __init__

4 Repeatability Evaluation

5 cases, figures, tables

4.1 Tables

- What elements of the paper are included in the REP (e.g.: specific figures, tables, etc.).
- Instructions for installing and running the software and extracting the corresponding results.

4.2 Figures

4.3 Fine-Tuning Figure and Table

References

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3. Prajna, S., Jadbabaie, A.: Safety verification of hybrid systems using barrier certificates. In: Proceedings of the 7th International Workshop on Hybrid Systems: Computation and Control HSCC. pp. 477–492 (2004)
4. Zeng, X., Lin, W., Yang, Z., Chen, X., Wang, L.: Darboux-type barrier certificates for safety verification of nonlinear hybrid systems. In: Proceedings of the 13th International Conference on Embedded Software. pp. 11:1–11:10. EMSOFT '16, ACM (2016)