

DeepSaucer: Verification Environment for Deep Neural Networks

NAOTO SATO^{1,a)} HIRONOBU KURUMA¹ MASANORI KANEKO¹ YUICHIROH NAKAGAWA¹
HIDETO OGAWA¹ THAI SON HOANG² MICHAEL BUTLER²

Abstract: In recent years, a number of methods for verifying DNNs have been developed. Because the approaches of the methods differ and have their own limitations, we think that a number of verification methods should be applied to a developed DNN. To apply a number of methods to the DNN, it is necessary to translate either the implementation of the DNN or the verification method so that one runs in the same environment as the other. Since those translations are time-consuming, a utility tool, named DeepSaucer, which helps to retain and reuse implementations of DNNs, verification methods, and their environments, is proposed. In DeepSaucer, code snippets for loading DNNs, running verification methods, and creating their environments are retained and reused as software assets in order to reduce the cost of verifying DNNs. The feasibility of DeepSaucer is confirmed by implementing it on the basis of Anaconda®, which provides a virtual environment for loading a DNN and running a verification method. In addition, the effectiveness of DeepSaucer is demonstrated by an use case example.

1. Introduction

Machine-learning technologies are being gradually introduced in various industrial fields. Among them, deep neural networks (DNNs) are being popularly applied. If DNNs are used in safety-critical applications, their behaviors should be carefully verified from several perspectives. In recent years, a number of methods for verifying DNNs have been developed. For example, metamorphic testing [1] is one useful way to evaluate the execution results of DNNs in the case that a test oracle does not exist. In metamorphic testing, metamorphic relations (which are necessary properties of a DNN in relation to multiple input values and their expected output values) are used as pseudo oracles. As another example, neuron-coverage testing [2] [3] [4] focuses on activation of neurons in a DNN. Test cases are collected or generated so as to activate neurons that were not activated in the previous testing. One of the advantages of neuron-coverage testing is that it can be applied systematically; that is, it is not necessary to find certain properties (like metamorphic relations) depending on the specification of the DNN. Moreover, some work on formal verification of DNNs by using SMT (satisfiability modulo theories) or LP (linear programming) solvers have been reported [5][6]. [7] The basic notion of formal verification of DNNs is encoding a DNN and its necessary property as a logical formula with the theory of real arithmetic. Solving that formula indicates whether the property is satisfied.

The authors do not believe that one method is enough for assuring the behavior of DNNs because the approaches of each

method are different and have limitations. Therefore, we think that a number of verification methods should be applied to a developed DNN. However, implementation of these methods often depends on the implementation environment, such as versions of Python (e.g., Python2 and Python3), the machine-learning framework (e.g., Tensorflow™ and Chainer®), and the package libraries. Moreover, the DNN to be verified should be loaded in the same environment as that of the verification method. Thus, to apply a number of methods to the DNN, it is necessary to translate either the implementation of the DNN or the verification method so that one runs in the same environment as that of the other. As well as DNNs, the datasets used for testing must also be transformed to be consistent with the implementation of the DNN and the verification method.

Since those translations and transformations are time-consuming, it would be useful if the implementations could be retained and reused for future development. Therefore, we provide a utility tool named *DeepSaucer*, which helps to retain and reuse implementations of DNNs, verification methods, datasets, and their environments.

2. Concepts

When a trained model of a DNN (simply called ‘model’ hereafter) is verified, code including procedures for loading the trained model, loading the dataset to be used for verification, and running a verification function are usually developed together. Among the procedures, those for loading the dataset and running the verification function can be reused for checking a different model. In addition, the procedure for loading the model can be reused for checking the same model with a different dataset or with a different verification function. Therefore, DeepSaucer re-

¹ Research & Development Group, Hitachi, Ltd.

² School of Electronics and Computer Science, University of Southampton

^{a)} naoto.sato.je@hitachi.com

tains code snippets of these procedures separately as software assets. In this way, it promotes reuse of the procedures and makes it possible to reduce the cost of the verification.

Moreover, to execute certain code snippets, it is necessary to set up corresponding environments. For example, if version 1.9 of TensorFlowTM is required to run those code snippets, but version 1.8 is installed in the current environment, it is necessary to upgrade to 1.9, and resolve conflicts if they occur. Therefore, as for DeepSaucer, scripts to automatically set up environments for the code snippets are also retained and reused as software assets. It is thus possible to reduce the cost of building the required environment. The key concepts of DeepSaucer are listed as follows:

- (1) Code snippets of loading trained models, loading datasets, and running verification functions are retained and reused as software assets in order to reduce cost of verifying DNNs
- (2) Scripts to create environments automatically are also retained and reused to prevent the environmental requirements from being ambiguous or insufficient and to reduce cost of building required environments.

3. Implementation

DeepSaucer is implemented on the basis of Python 3.6 provided by Anaconda[®]. The architecture of DeepSaucer is shown in Fig. 1. As code snippets mentioned in Section 2, DeepSaucer

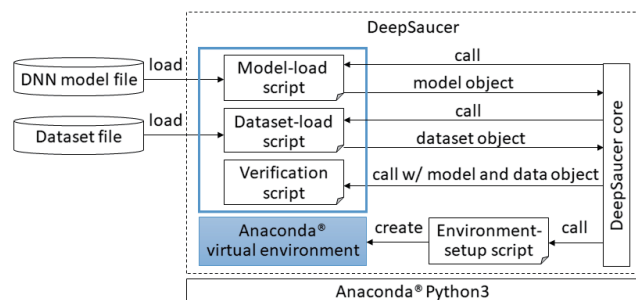


Fig. 1 Software architecture of DeepSaucer

retains Python scripts for loading models, loading datasets for testing, and executing verification functions. They are called *model-load script*, *dataset-load script*, and *verification script* respectively. A user selects one of them to be executed. A model-load script is called by the DeepSaucer core. Typically, a model-load script refers to a particular file containing information about a trained model. Then, the model-load script returns a trained DNN model to the DeepSauce core. Similarly, a dataset-load script is called by the DeepSaucer core. The dataset-load script returns the corresponding dataset that was transformed appropriately. After running the model-load script and dataset-load script, a verification script is called by the DeepSaucer core. The verification script executes a particular verification function with the loaded model and dataset.

The model-load script, dataset-load script, and verification script (hereafter, all called ‘functional scripts’) are basically expected to be written in Python. However, it is allowed that a functional script requires a different environment. When a functional script is loaded in DeepSaucer, it is associated with an *environment-setup script* by a user; consequently, an Anaconda[®]

virtual environment is created, and necessary package libraries appropriate for the corresponding functional script are installed in that environment. The model-load script, dataset-load script, and verification script can be selected for running the verification only if they are associated with the same environment-setup script. Before the DeepSaucer core runs the selected functional scripts, it calls the associated environment-setup script. It is assured that DeepSaucer runs on Ubuntu 17.10 with Python 3.6 provided by Anaconda[®] 5.2.

4. Use case example

It is assumed that a DNN model was developed and it is necessary to check it by several verification methods. DeepSaucer retains a number of verification scripts and the corresponding datasets used in past projects. It is also assumed that Chainer[®] on Python 2.7 was chosen in the current project (although TensorFlowTM on Python 3.6 was adopted in the past projects). In that case, verification scripts retained in DeepSaucer is not applicable to the current model directly. Therefore, parameters (such as weight and bias) of the model developed in Chainer[®] based on Python 2.7 are first saved as a file. Second, a model-load script that reads the saved file and returns the model of TensorFlowTM is developed on Python 3.6. Finally, by running the existing verification scripts with the model, the model is successfully verified. In such a situation, DeepSaucer promotes the reuse of existing verification scripts. Moreover, since it shows a list of verification scripts used in the past projects, which verification scripts are reusable is easy to understand.

5. Conclusion

We have developed a utility tool, called DeepSaucer, for verifying DNNs. DeepSaucer helps to retain and reuse implementations of DNNs, verification methods, datasets, and their environments. The feasibility of DeepSaucer is confirmed by implementing it on the basis of Python 3.6 provided by Anaconda[®]. As for future work, the effectiveness of DeepSaucer will be evaluated in actual developments of DNNs. Moreover, our implementation using Anaconda[®] will be compared with other implementations based on other virtualization tools like Docker[®].

References

- [1] T. Y. Chen, F.-C. Kuo, H. Liu, P. L. Poon, D. Towey, T. H. Tse, and Z. Q. Zhou.: Metamorphic Testing: A Review of Challenges and Opportunities. *ACM Computing Surveys* 51,1 (2018).
- [2] Y. Tian, K. Pei, S. Jana, and B. Ray.: DeepTest: Automated Testing of Deep-Neural-Network-driven Autonomous Cars, *ICSE’2018 Technical Papers* (2018).
- [3] K. Pei, Y. Cao, J. Yang, and S. Jana.: DeepXplore: Automated White-box Testing of Deep Learning Systems, *The 26th ACM Symposium on Operating Systems Principles* (2017)
- [4] Y. Sun, X. Huang, and D. Kroening.: Testing Deep Neural Networks, *arXiv:1803.04792* (2018).
- [5] X. Huang, M. Kwiatkowska, S. Wang, and M. Wu.: Safety Verification of Deep Neural Networks, *Computer Aided Verification 2017, Lecture Notes in Computer Science*, vol 10426, pp.3-29 (2017).
- [6] G. Katz, C. Barrett, D.L. Dill, K. Julian, and M.J. Kochenderfer.: Replex: An Efficient SMT Solver for Verifying Deep Neural Networks, *Computer Aided Verification 2017*, pp.97-117 (2017).
- [7] R. Ehlers.: Formal verification of piece-wise linear feed-forward neural networks. *Automated Technology for Verification and Analysis 2017* (2017).