



北京大学

博士研究生学位论文

题目：深度学习系统的覆盖测试
与全局验证

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摘要

近年来，深度学习系统开始在越来越多的领域得到应用。此类系统利用神经网络进行搜索、推荐、决策、特征提取，并在计算机视觉、自然语言处理等诸多前沿领域取得了可以媲美甚至超越人类的性能。然而，深度学习系统在医疗诊断、自动驾驶等安全攸关领域的部署也引发了公众对其正确性、鲁棒性等方面的忧虑。尤其是随着对抗攻击被发现以及一系列令人痛心的事故的发生，业界开始认识到深度学习系统与传统软硬件系统一样，面临严峻的安全可信问题，亟待更严格、系统的方法来保障其在安全攸关领域的应用。

深度学习系统与传统软硬件系统行为具有显著区别，为其可信性保障带来了巨大的挑战。例如，深度学习系统本质上遵循数据驱动的编程范式，缺乏显式的控制流；深度学习系统具有涌现性，系统整体行为的复杂性远远大于其组成单元行为的简单累加；深度学习系统往往具有庞大的输入空间，而对抗反例普遍分布在输入空间中，难以被传统的验证方法全部找出，等等。以上这些特点使得传统软硬件系统的认证方法往往难以直接迁移到深度学习系统上，严重限制了现有深度学习可信性保障方法的可用性。本论文从深度学习系统自身的特性出发，对深度学习系统的测试和形式化验证方法进行研究。其中测试是对系统进行可信性分析最普遍的轻量级手段，在系统部署应用前能够有效暴露其中潜在的问题和漏洞，以保障系统的安全性；而形式化验证是与测试互补的一种重量级技术，能为系统提供完备的可信性保障。论文包括如下三部分内容：深度学习系统覆盖测试的有效性、神经网络覆盖准则的改进、及前馈神经网络的全局鲁棒性验证。

论文第一部分探索了深度学习系统覆盖测试标准在度量测试充分性和提升深度学习系统鲁棒性方面的有效性，并提出了新的覆盖测试标准。受传统软件测试方法的启发，人们提出了各种基于不同覆盖标准的测试方法来保证深度学习系统的安全性。但在相关研究中，覆盖测试标准在对抗攻击、寻找神经网络漏洞等方面的有效性受到质疑。本文指出了两个适合覆盖测试标准的应用领域：1) 评估不同测试集的测试充分性，2) 引导数据增强来提升深度学习系统的鲁棒性，并从这两个方面的实验表现评价了覆盖测试标准的性能。评估结果表明覆盖测试标准在这两个方面的有效性，且我们提出的新神经元覆盖标准在这两方面都优于其他主流的覆盖测试标准。

论文的第二部分提出了加速并细化深度学习系统覆盖测试的框架。已有的深度学习系统覆盖测试标准要么不够精确，无法捕捉神经网络的微妙行为，要么时间代价过高，无法部署在大规模的神经网络上，很难平衡测试充分性评价的质量和效率。此外，

主流的覆盖测试标准在测试套件规模上缺乏“可扩展性”，当评估的测试套件规模过大或过小时，其性能都不符合深度学习系统的测试实践。在本文中我们提出了使用哈希加速的组合覆盖深度学习系统测试框架。该框架利用哈希加密函数对激活状态分析进行加速，同时赋予主流的覆盖标准传递性和组合性以细化其评估粒度并提升其可扩展性。框架将组合覆盖测试的时间复杂度从多项式时间降低到线性时间，从而能够部署在更大规模神经网络上，并且能获得更敏感的测试充分性评估能力。

论文的第三部分提出了可变粒度的深度学习系统覆盖测试标准。覆盖测试标准被应用于评估深度学习系统测试充分性、寻找极端情况、指导测试样例的选择、辅助数据增强等领域。不同的用途对覆盖测试标准的粒度提出了不同的要求，例如评估测试充分性需要粒度尽可能细的覆盖测试标准，而指导测试样例选择需要覆盖测试标准以较粗的粒度给出少量的高价值候选样例。为了给不同种类任务提供通用的覆盖测试标准，本文提出了可变粒度深度学习系统覆盖测试标准 HeatC。该标准从神经网络中提取基于类激活图的特征，并聚类特征来生成测试目标。实验表明，HeatC 在评估测试套件的充分性和从无标注数据集中挑选高价值测试样例方面的表现均优于现有主流覆盖标准。

论文的第四部分提出了全局鲁棒性可验证的深度学习框架。现有的深度学习对抗攻击技术是不完备的，难以在无法找到对抗反例时保障神经网络本身的安全性。而现有的深度学习验证工作多集中于局部鲁棒性，例如指定输入空间中的可行域，分析其在输出空间中的可达性。对于主流的深度学习任务来说，在高维输入空间中指定可行域本身就是“预言家难题”，因为如果我们能在输入空间中以某种简单约束的形式划出某个类别的可行域，那我们就不需要这个深度学习系统。针对这一问题，我们开发了一个深度学习系统全局鲁棒性验证框架 DeepGlobal，该框架包含一个通过符号执行寻找网络潜在边界的规则生成器，以及一个能将规则生成代价降低到多项式时间的神经网络架构。DeepGlobal 从生成的潜在边界中选择神经网络在执行时真实生效的边界，并进一步在边界上寻找非噪声的输入，从而发现会被对抗攻击威胁的边界。

本论文的研究内容为深度学习系统的安全分析及针对对抗攻击的鲁棒性验证技术。给出了一套基于神经网络覆盖测试和全局鲁棒性验证技术的深度学习系统可信保障框架，通过测试与形式化验证的结合，为深度学习系统面临的可信性、安全性问题提供具有高度可扩展性的解决方案，对深度学习系统在安全攸关领域的应用及可信深度学习的发展有重要意义。

关键词：深度学习系统，覆盖测试，全局验证

Coverage Testing and Global Verification of Deep Learning Systems

Weidi Sun (Applied mathematics)

Directed by: Prof. Meng Sun

ABSTRACT

In recent years, deep learning (DL) systems have been applied in more and more fields. Such systems use neural network for search, recommendation, decision, feature extraction, etc., and have achieved performance comparable to or even surpassing human beings in many frontier fields such as computer vision and natural language processing. However, the deployment of DL systems in safety-critical areas such as medical diagnosis and autonomous driving has raised public concerns about its correctness and robustness. Especially with the discovery of adversarial attacks and a series of distressing accidents, the industry has realized that DL systems, like traditional hardware and software systems, face serious security and trustworthiness problems. Rigorous and systematic methods are urgently needed to ensure DL systems' application in security-critical fields.

The behaviors of DL systems are significantly different from those of traditional software and hardware systems, which brings great challenges to DL systems' reliability. For example, DL systems inherently follow a data-driven programming paradigm and lack explicit control flow; DL systems are emergent, and the complexity of their overall behavior is much greater than the simple accumulation of their unit-level behaviors' complexity; DL systems have huge input space containing pervasively distributed adversarial examples, and traditional verification methods can hardly find all these adversarial examples etc. The aforementioned challenges make it difficult to directly migrate the certification methods of traditional software and hardware systems to DL systems, and seriously limit the availability of the existing DL trustworthiness assurance methods. Therefore, this thesis aims to investigate testing and formal verification of the DL systems based on their own characteristics. Testing is the most common light-weight method for trustworthiness guarantee of large-scale DL systems. It can effectively expose the potential problems and vulnerabilities before the deployment, so as to guarantee the trustworthiness of systems. Formal verification is a heavy-weight method which

is complementary to testing. It can provide complete trustworthiness assurance for DL systems. This thesis includes the following three parts: the validity of coverage testing for DL systems, the improvement of neural networks' coverage criteria, and the global robustness verification of feedforward neural networks.

The first part of this thesis explores the validity of DL coverage criteria in two aspects, measuring test adequacy and improving the robustness of DL systems, and proposes a new coverage testing criterion. Inspired by the traditional software engineering testing, testing methods based on various coverage criteria have been proposed to ensure the safety of DL systems. However, the validity of coverage criteria in the adversarial attack, finding vulnerabilities, and other applications has been questioned in related researches. This thesis points out two areas suitable for coverage criteria: 1) evaluating test adequacy of different test sets, 2) guiding data augmentation to improve the robustness of DL systems, and evaluates the performance of coverage criteria via the experiment in these two aspects. The evaluation results show the validity of coverage criteria in these two areas, and our novel coverage criterion is superior to other mainstream criteria in these two aspects.

The second part of this thesis proposes a framework for accelerating and refining coverage testing. Existing coverage criteria are either not fine enough to capture the subtle behavior of neural networks, or too time-consuming to be deployed on large-scale neural networks, which can hardly balance the quality and efficiency of test adequacy evaluation. In addition, some mainstream coverage criteria lack "scalability" regarding test suite size. Their performance does not conform with DNN testing practice when the scale of the evaluated test suite is too big or small. In this thesis, a combinatorial coverage testing framework with hash acceleration is proposed. The framework utilizes cryptographic hash functions to speed up the analysis of activation states, and makes mainstream coverage criteria transitive and combinatorial to refine their evaluation granularity and improve their scalability. The framework reduces the time complexity of combinatorial coverage testing from polynomial time to linear time, enabling its deployment on larger-scale neural networks and more sensitive test adequacy evaluation.

The third part of this thesis presents a variable-grained DL coverage criterion. Coverage criteria are applied to many areas, such as evaluating the test adequacy of deep learning systems, finding corner cases, guiding the selection of test samples, assisting data augmentation, etc. Different applications require coverage criteria with different levels of granularity. For example, the coverage criteria for evaluating the test adequacy need to be as fine-grained as possible, while guiding the test sample selection requires the coverage criteria to provide a

small number of high-value candidates at a coarser granularity. To provide a common coverage criterion for different tasks, this thesis proposes a variable-grained DL coverage criterion: HeatC. It extracts class-activation-map-based features from neural networks, and clusters the features to generate test targets. HeatC outperforms existing mainstream coverage criteria in assessing the adequacy of test suites and selecting high-value test samples from unlabeled dataset.

The fourth part of the thesis proposes a DL framework for global robustness verification. The existing DL adversarial attack technologies are incomplete, as they cannot guarantee the safety of neural networks when adversarial examples cannot be found. Meanwhile, existing DL verification works mostly focus on local robustness, such as analyzing the output space reachability of a specified feasible region in input space. For mainstream DL tasks, specifying a feasible region in a high-dimensional input space is an “Oracle Problem”, because if we can specify the feasible regions of a certain category in the input space in the form of simple constraints, we do not need the DL systems. To address this problem, a framework for global robustness verification of DL systems named DeepGlobal is developed in this part. DeepGlobal has a rule generator that finds the potential boundaries of the network via symbolic execution, and a neural network architecture that reduces the cost of rule generation to polynomial time. From the generated potential boundaries, DeepGlobal selects the real boundaries taking effect in the execution of the neural network, and searches for non-noise inputs around the real boundaries to find the adversarial dangerous boundaries.

The research contents of this thesis consist of the safety analysis of DL systems and robustness verification techniques against adversarial attacks. A trustworthiness assurance framework based on neural network coverage testing and global robustness verification is proposed, which provides highly scalable solutions to the credibility and safety problems faced by DL systems through the combination of testing and formal verification. It is of great significance to the application of DL systems in safety-critical fields and the development of trustworthy DL systems.

KEY WORDS: Deep Learning Systems, Testing, Coverage Criteria, Formal Verification

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攻读博士期间发表的论文及其他成果

个人简介

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专利

1. 一种屏幕翻拍检测方法, 孙纬地, 郭烽, 苏晓东, 字节跳动 (已受理)
2. 一种从像素化明水印图像中还原文本信息的技术, 孙纬地, 郭烽, 苏晓东, 字节跳动 (已受理)
3. 针对压缩退化明水印图像的复原技术框架, 孙纬地, 郭烽, 苏晓东, 字节跳动 (已受理)

获奖情况

1. 2022年10月. 斯伦贝谢奖学金
2. 2022年9月. 校级三好学生
3. 2022年6月. 校长奖学金
4. 2020年6月. 学院奖学金

5. 2020年6月. 优秀科研奖
6. 2019年6月. 学院奖学金

参与项目

1. 2022-2025, 深度学习系统的可信性保障
2. 2021-2022, 大规模深度学习系统形式化建模与验证
3. 2019-2021, 高可信深度学习: 理论与技术

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“不知我等是狂是愚，唯知一路向前奔驰。”

