Safety and Reliability of Deep Learning

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ABSTRACT

Robotics and Autonomous Systems (RAS) become ever more relying on deep learning components to support their perception and decision making. Given RAS will inevitably be applied to safety critical applications, efforts are needed to ensure that the deep learning is safe and reliable. In this lecture, I will give a brief overview on recent progress in the verification and validation techniques for deep learning, focusing on two major safety and reliability risks, i.e., robustness and generalisation. We consider formal verification, statistical evaluation, reliability assessment, and runtime monitoring techniques, all of which complement with each other in providing assurance to the reliability of deep learning in operation. The challenges and future directions will also be discussed.

CCS CONCEPTS

• Software and its engineering → Software verification and validation; **• Theory of computation → Machine learning theory**.

KEYWORDS

safety, reliability, neural networks, verification, validation

For robotics and autonomous systems (RAS) that are designed to work with real-world applications, deep learning becomes necessary for its ability to implement – by learning from massive data – complex functions that are hard to be programmed directly. Effective approaches are therefore called for to show whether or not a deep learning component is safe and reliable. Deep learning is an over-parameterised function learned from a set of data by minimising a loss function. Unlike traditional systems, deep learning is not developed in a way that can fully take into consideration specifications other than the accuracy [21]. This makes verification and validation (V&V) methods, which are independent from the design and implementation, become more important than ever.

This lecture will focus on the V&V methods for reliability, which requires the deep learning to function correctly for a period of time. As suggested in [25, 26], we believe the reliability of deep learning is actually determined by two currently intensively-studied risks, i.e., Reliability = Robustness × Generalisation. Albeit learned from a known dataset, deep learning is expected to work well on unknown, or unseen, data. Generalisation error measures the gap between a deep learning model's performance on known and unknown data. Robustness error appears when a decision (e.g., a classification) is changed over an invisible perturbation to the input.

In the following sections, I will review a few categories of V&V methods that have been explored in order to deal with the reliability of deep learning. Please refer to [10] for a comprehensive review.

1 FORMAL VERIFICATION

Formal verification requires mathematically rigorous proof to argue for or against the satisfiability of a property on a given deep learning model. Existing verification algorithms are mainly focused on point-wise robustness, i.e., the robustness of the model over a given input. The algorithms can be roughly categorised into constraint-solving based methods [13], abstract interpretation based methods [5, 14], global optimisation based methods [11, 15, 16], and game-based methods [23, 24]. The first two categories treat the deep learning as a white-box, with the computation needed on all neurons. This results in the scalability issue due to the complexity of the problem and the size of the deep learning. The latter two categories can work with real-world deep learning, but are still subject to the curse of dimensionality.

The difficulties of formal verification have led to the development of other V&V methods, as described below.

2 STATISTICAL EVALUATION

Statistical evaluation applies statistical methods in order to gain insights into the verification problem we concern. In addition to the purpose of determining the existence of failures (i.e., counterexamples to the satisfiability of desirable properties) in the deep learning model, statistical evaluation assesses the satisfiability of a property in a probabilistic way, by e.g., aggregating sampling results. The aggregated evaluation result may have probabilistic guarantee, in the form of e.g., the probability of failure rate lower than a threshold l is greater than $1 - \epsilon$, for some small constant ϵ.

For the robustness, sampling methods and testing methods have been considered. Sampling methods, such as [22], are to summarise property-related statistics from the samples. Testing methods, on the other hand, generate a set of test cases and use the generated test cases to evaluate the reliability (or other properties) of deep learning. There are a number of ways to determine how the test cases are generated, including e.g., fuzzing, coverage metrics [8, 18], symbolic execution [6], concolic testing [19], etc. While sampling methods can have probabilistic guarantees via e.g., Chebyshev's inequality, it is still under investigation on how to associate test coverage metrics with probabilistic guarantee.

For the generalisation error, other than the empirical approach of using a set of test data to evaluate, recent efforts on complexity measure [3, 12] suggest that it is possible to estimate generalisation error – with theoretical bound – by only considering the weights of the deep learning without resorting to the test dataset.

3 PROBABILISTIC ASSESSMENT AND SAFETY ARGUMENT

While the above techniques may compute the (un)satisfiability of a property as well as its associated evidence, the specifications they work with are usually low-level ones, such as the point-wise robustness which only concerns the robustness w.r.t. a given input. It is needed to understand if and how the evidence to these low-level specifications can contribute to the claim of higher-level reliability specification such as “a deep learning model can be free from failure for the next k inferences”. In [25], we show how to develop a principled safety argument to justify the reliability claim by aggregating evidence from either formal verification or statistical evaluation with Bayesian inference [17]. Due to the unknown ground truth over the underlying data distribution, this approach usually requires to either make an assumption over the distribution [22] or learn the distribution [26]. Note that, the obtained probabilistic assessment can be bounded [2, 12].

One step further, it might be interesting to understand, and verify, the safety and reliability issues in learning-enabled autonomous systems where deep learning components interact with symbolic or probabilistic components [9, 20].

4 RUNTIME MONITORING

The above approaches require significant computation. Worse than that, a deep learning model might be applied to scenarios different from where the training data is collected. These suggest the need of a runtime monitor to determine the satisfiability of a specification on the fly.

Given the missing of specification, the current runtime monitoring methods for deep learning start from constructing an abstraction of a property, followed by determining the failure of the property by checking the distance between the abstraction and the original learning model. There are a few existing methods on abstraction of deep learning. For example, in [4], a Boolean abstraction on the ReLU activation pattern of some specific layer is considered and monitored. Conversely of Boolean abstraction, [7] consider box abstractions. In [1], we consider a Bayesian network based abstraction, which abstracts hidden features as random variables.

5 FUTURE CHALLENGES

V&V for deep learning is still in its infancy. All the above directions are still far from resolved and currently under intensive investigation. More future challenges will come from novel deep learning models and novel applications. Notably, continual learning suggests that a learning system may have to continuously update itself with the coming of new data or new tasks, and distributed learning, or more specifically federated learning, requires multiple agents to learn a global model with different sources of training data. How to extend the existing V&V approaches to these more involved deep learning models will be a significant challenge.

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