Extending Artificial Intelligence Verification and Validation to Coverage Properties

Keywords: Formal Verification, Neural Network, Why3, CAISAR

Institution

The French Alternative Energies and Atomic Energy Commission (CEA) is a key player in research, development, and innovation. Drawing on the widely acknowledged expertise gained by its 16,000 staff spanned over 9 research centers with a budget of 4.1 billion Euros, CEA actively participates in more than 400 European collaborative projects with numerous academic (notably as a member of Paris-Saclay University) and industrial partners. Within the CEA Technological Research Division, the CEA List institute addresses the challenges coming from smart digital systems.

Among other activities, CEA List's Software Safety and Security Laboratory (LSL) research teams design and implement automated analysis in order to make software systems more trustworthy, to exhaustively detect their vulnerabilities, to guarantee conformity to their specifications, and to accelerate their certification. Recently the field of activity of the laboratory has been extended to artificial intelligence safety and security verification.

Context

Critical systems are the next frontier for data-based Artificial Intelligence (AI) systems. Although their remarkable performance in a profusion of fields, deep neural networks lack the necessary guarantees to be embedded in critical systems. Defining the conformity of an AI system regarding a specification is an open research question (Mattioli et al. 2021). Specifically, formal verification is still struggling to be applied to realistic AI programs. The main issues are:

- the NP-completeness of formal neural network analysis (Katz et al. 2017)
- the lack of scalability of existing tools (SAT and SMT solvers, abstract interpretation...)
- the difficulty to formally specify the input distribution and specifications to assert the safety of an AI system (Girard-Satabin et al. 2020)

Over the last five years, those problems were investigated, leading to the birth (and death) of a profusion of tools and techniques (see for instance ERAN (Singh et al. 2018), CROWN (Wang et al. 2021), Reluplex (Katz et al. 2017) and its successor Marabou (Katz et al. 2019)).

Some of those tools rely on *reachability analysis*, that is to say, computing the possible range of outputs given a perturbation on the input. To check against such properties, the user is required to provide: * a set of accepted parametrized perturbations * some specification on the dataset to be checked against * an acceptable tolerance on the system possible misbehaviour

Moreover, other tools do not provide an unambiguous answer on the robustness of neural networks against a given perturbation; but rather display possible decrease in performance given some perturbations. In that case, there is an additional need to provide a semantic for robustness properties.

Objectives

The student will work with CAISAR, an AI verification platform currently developped in the lab. The goal is to provide a semantic for robustness properties and coverage testing properties for reachability analysis tools.

This internship can be described by the following goals:

- familiarization with the CAISAR platform, as well as with some state-of-the-art neural network analysis tools
- formalizing the properties of robustness and coverage for said tools
- provide an implementation of this semantic in CAISAR
- optionnaly, contributing to visualisation features

Qualifications

The candidate will work at the crossroads of formal verification and artificial intelligence. As it is not realistic to be expert in both fields, we encourage candidates that do not meet the full qualification requirements to apply nonetheless.

- **Minimal**
  - Master student or equivalent (2nd/3rd engineering school year) in computer science
  - notions of AI and neural networks
  - ability to work in a team, some knowledge of version control
- **Preferred**
  - knowledge of OCaml
  - knowledge of formal verification in general, of SMT solving in particular
  - knowledge of Why3

Characteristics

The candidate will be monitored by two research engineers of the team.

- **Duration:** 5 to 6 months from early 2023
- **Location:** CEA Nano-INNOV, Paris-Saclay Campus, France
- **Compensation:**
  - €700 to €1300 monthly stipend (determined by CEA compensation grids)
  - maximum €229 housing and travel expense monthly allowance (in case a relocation is needed)
  - CEA buses in Paris region and 75% refund of transit pass
  - subsidized lunches
  - 2 days of remote work

Application

If you are interested in this internship, please send to the contact persons an application containing:

- your resume;
- a cover letter indicating how your curriculum and experience match the qualifications expected and how you would plan to contribute to the project;
- your bachelor and master 1 transcripts;
- the contact details of two persons (at least one academic) who can be contacted to provide references.

Applications are welcomed until the position is filled. Please note that the administrative processing may take up to 3 months.

Contact persons

For further information or details about the internship before applying, please contact:

- Julien Girard-Satabin (julien.girard2@cea.fr) (also available on LinkedIn)
- Zakaria Chihani (zakaria.chihani@cea.fr)

References

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