CAISAR: A Platform for Characterizing Artificial Intelligence Safety and Robustness

AISafety 2022

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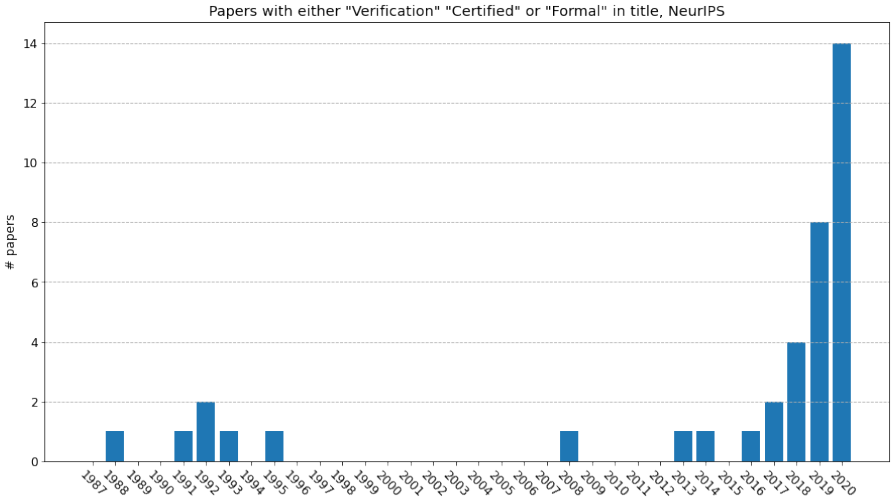
Formal verification for machine learning



Adapted from `https://github.com/nemanja-rakicevic/conference_historical_data_analysis`

Non-exhaustive list of tools

Include only the latest "version" (including extensions and rebranding)

- Marabou [Kat+19]
- Neurify
- ERAN [Sin+19; Mül+21]
- $\alpha - \beta$-Crown [Wan+21]
- Nnenum [Bak21]
- NNV (https://github.com/verivital/nnv)
- FaceLattice (https://arxiv.org/abs/2003.01226, https://github.com/verivital/FaceLattice)
- Facet-Vertex incidence (https://github.com/Shaddadi/Facet-Vertex-FFNN)
- Veritex (https://github.com/Shaddadi/veritex)
- Verinet and Venus (https://github.com/vas-group-imperial/VeriNet)

Non-exhaustive list of tools

Include only the latest ”version” (including extensions and rebranding)

- ReluDiff (https://arxiv.org/abs/2001.03662, https://github.com/pauls658/ReluDiff-ICSE2020-Artifact)
- Peregrinn (https://arxiv.org/abs/2006.10864, https://github.com/rcpsl/PeregriNN)
- Oval (https://github.com/oval-group/oval-bab)
- Libra [Urb+19]
- MIPVerify [TXT19]
- Planet [Ehl17]
- Sherlock [Dut+17]
- ZoPE (https://arxiv.org/abs/2106.05325,https://github.com/sisl/NeuralPriorityOptimizer.jl)
- DNNV [SED21]

(credits: Bill Wurtz)

Lots of tools increases burden of choice

Which tool to choose?

How to encode a given problem for multiple tools?

Could we specify a verification problem independently of the tool?

A new, thriving ecosystem

Selective pressure

Short lifetime of tools: Reluplex to Marabou, AI^2 to ERAN, Fast-Lin to $\alpha - \beta$-CROWN

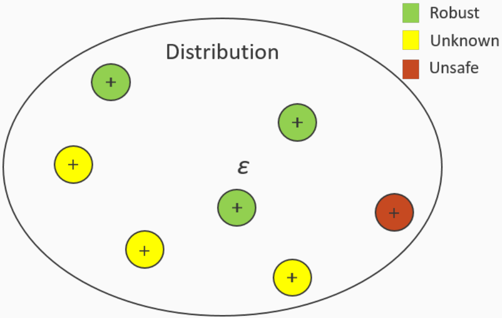
Ecological niches: from fully-connected neural networks to state-of-the-art architectures, by way of SVMs

Collaboration

Collaborative initiatives: VNN-COMP or VNNLib

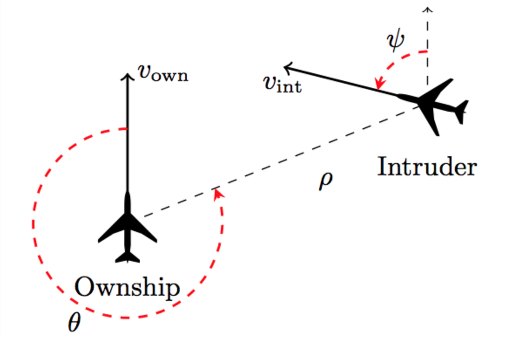
Cross-fertilization of techniques across tools: symbolic propagation [Li+19; Sun+18; HL20; Wan+21], efficient space parititionning [Urb+19; Gir+21], mixing exact solvers and fast bound propagation [Gil+18; Fer+22]

Families of properties according to the literature



local robustness: given x_0

$\forall x, dist(x - x_0) < \varepsilon \implies f(x) = f(x_0)$



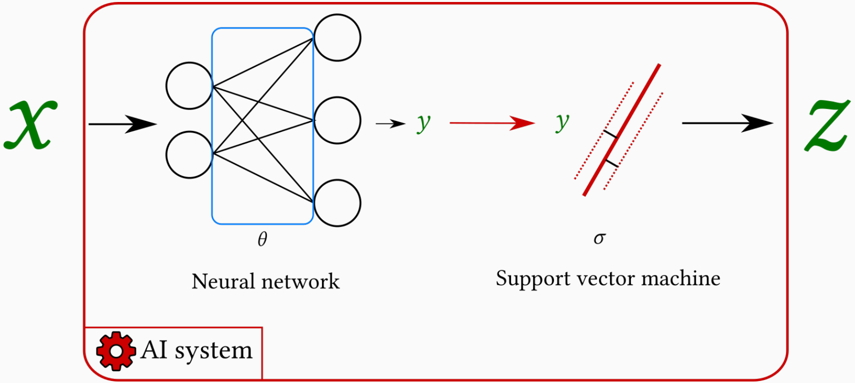
clearly defined semantics *à la* ACAS

global properties on low-dimensional programs

Existing benchmarks: ACAS-like and local adversarial robustness?

What about characterizing privacy? Fairness? Symmetry relations? How to phrase custom properties for provers that are not designed to?

Handling complex systems?



How to compose system components in the analysis?

Three interesting venues

1. tool-independant modelling
2. flexibility in problem statement
3. composition of components

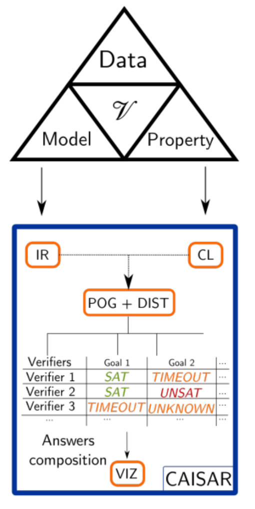
CAISAR

platform for Characterizing Artificial Intelligence Safety And Robustness

A platform building from principled and industrial-tested techniques

Written in OCaml, using Why3 as backend

Overall architecture of CAISAR



Supports SMT and abstract interpretation reasoning (Marabou, PyRAT, SAVer), and soon metamorphic testing (AIMOS)

WhyML language: composition

free component composition

tool independent modelling

```
theory T
 use Net.NNasTuple
 use SVM.SVMAsArray
 use ieee_float.Float64
 use caisar.NN

 goal G: forall x1 x2 x3.
  (0.0:t) .< x1 .< (0.5:t) ->
  let (y1,y2) = Net.net_apply x1 x2 x3 in
  let (z1,z2) = SVM.svm_apply y1 y2 in
    (0.0:t) .< z1 .< (0.5:t)
    /\
    (0.0:t) .< z2 .< (0.5:t)
end
```

WhyML language: expressivity

first-order language with polymorphic types, pattern matching, and inductive properties capabilities
modelization freedom to define a vast set of property

```
predicate dist_linf
  (a: input_type)
  (b: input_type)
  (eps:t)
  (n: int) =
  forall i. 0 <= i < n ->
    .- eps .< a i .- b i .< eps

predicate robust_to
  (model: model)
  (a: input_type)
  (eps: t) =
  forall b. dist_linf a b eps
  model.num_input ->
  model.app a = model.app b
```

Future work

- support more prominent verifiers (among ERAN, nnenum) as well as VNNLib/SMTLIB format
- how to compose several verifiers techniques (metamorphic tests plus formal verification)?
- how to choose the proper prover heuristics? more generally, how to refine and adapt proof strategies according to one's need?

CAISAR

Libre software under LGPLv2 at `https://git.frama-c.com/pub/caisar`

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