Neural Network Verification With Vehicle: Chapter 1 - Introduction

VeTSS Summer School'23

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The Vehicle Team


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Ben Coke


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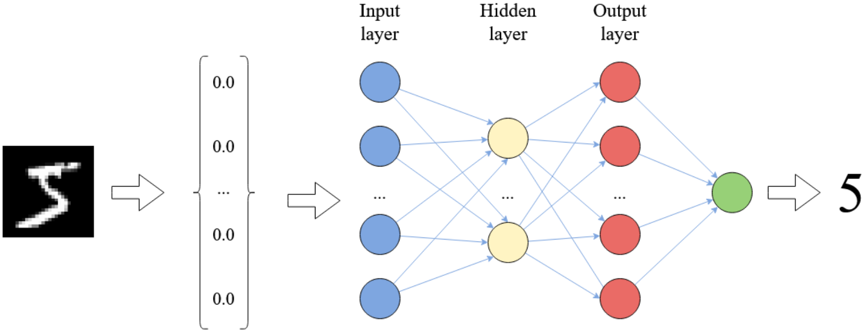
Wen Kokke


Marco Casadio


Katya K

Neural nets for classification



Formally,

a neural network is a function $N : R^n \to R^m$.

Neural networks

... are ideal for "perception" tasks:

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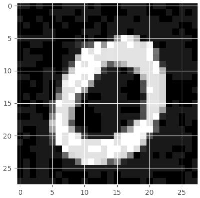
  adversarial attacks
  data poisoning
  catastrophic forgetting

One example: Adversarial Attacks



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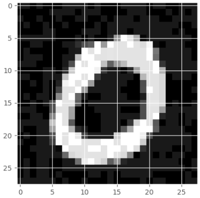

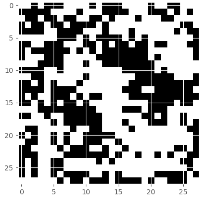

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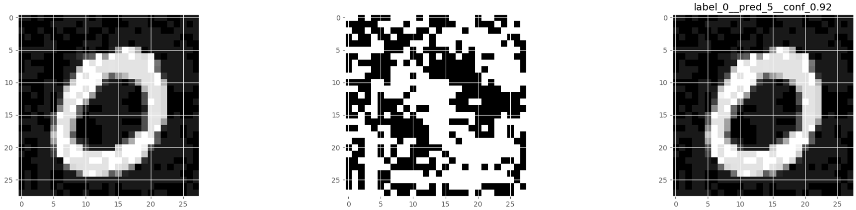

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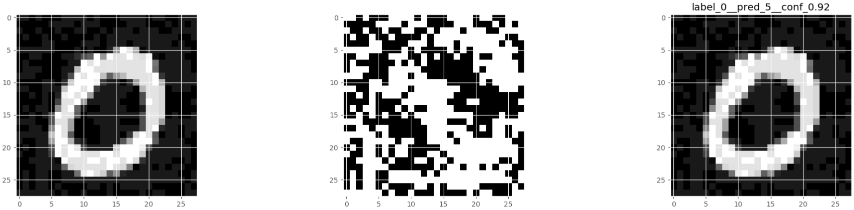

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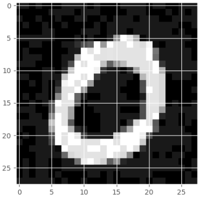

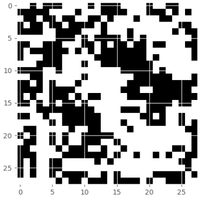

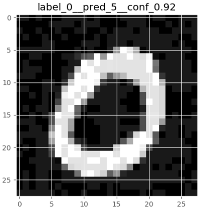

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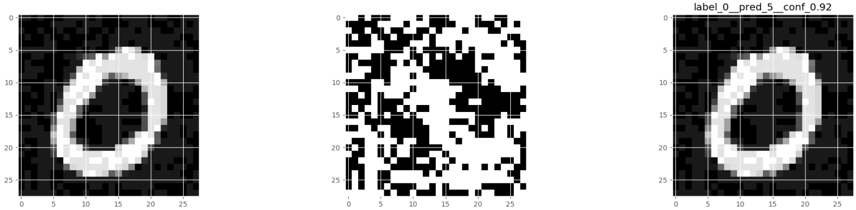
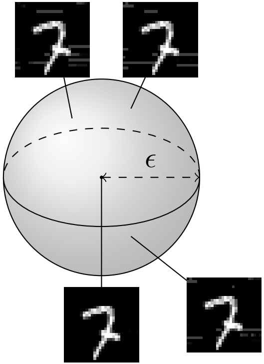


the perturbations are imperceptible to human eye

attacks transfer from one neural network to another

affect any domain where neural networks are applied

Verification Property: "ϵ-ball robustness"



An ϵ-ball $\mathbb{B}(\hat{\mathbf{x}}, \epsilon) = \{\mathbf{x} \in \mathbb{R}^n : |\hat{\mathbf{x}} - \mathbf{x}| \leq \epsilon\}$

Classify all points in $\mathbb{B}(\hat{\mathbf{x}}, \epsilon)$ "robustly".

Another example property: ACAS Xu

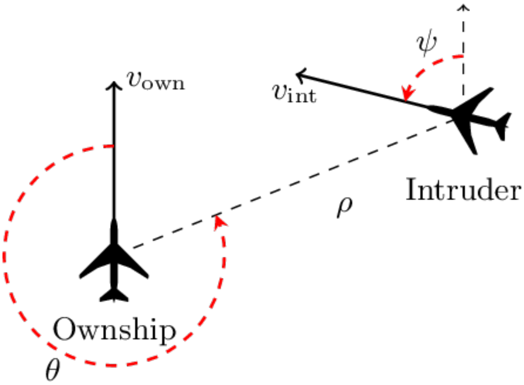
A collision avoidance system for unmanned autonomous aircraft.

Inputs:

- Distance to intruder, ρ
- Angle to intruder, θ
- Intruder heading, φ
- Speed, v_{own}
- Intruder speed, v_{int}

Outputs:

- Clear of conflict
- Strong left
- Weak left
- Weak right
- Strong right



ACAS Xu

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Definition (ACAS Xu: Property 1)

If the intruder is distant and is significantly slower than the ownship, the score of a COC advisory will always be below a certain fixed threshold.

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Definition (ACAS Xu: Property 1)

If the intruder is distant and is significantly slower than the ownship, the score of a COC advisory will always be below a certain fixed threshold.

$$(\rho \geq 55947.691) \wedge (v_{own} \geq 1145) \wedge (v_{int} \leq 60)$$
$\Rightarrow$ the score for COC is at most 1500

More Generally

Given $N : R^n \rightarrow R^m$

Verification of such functions most commonly boils down to specifying admissible intervals for the function's output given an interval for its inputs.

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Casadio, M., Komendantskaya, E., Daggitt, M.L., Kokke, W., Katz, G., Amir, G., Refaeli, I.: Neural network robustness as a verification property: A principled case study. In: Computer Aided Verification (CAV 2022).

Overview of The Verification Landscape

2011 — 2013 — 2015 — 2017 — 2019 — Now

2011: First NN Verification Tool Pulina and Tacchella (2011)

2013: First Adversarial Attack Baggio et al (2013)

Panda Gibbon Paper Szegedy et al. (2013)

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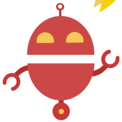
Notion of Adversarial Robustness Fawzi A. (2015)

I have this specification

I want to verify!



What tools are available?
2015

approximate

adverserial

complete

others

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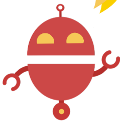

What tools are available? 2017

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2019: Dozens and Dozens more!

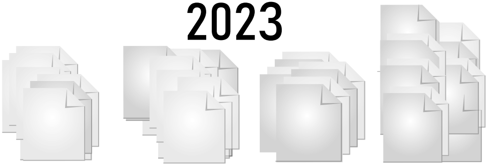
First Multi Backend Tool Guidotti et al (2020)

Now: ...

I have this specification I want to verify!

property specification

What tools are available? 2023



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Current Verifier Landscape

A whole range of domain-specific verifiers exist:

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- Verisig (interval arithmetic)
- AlphaBetaCROWN (linear bound propagation)
- ...

International Standards and Competitions

https://www.vnnlib.org/

Current Verifier Landscape

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Marabou is our current choice as it is complete, and the set of expressible queries is large!

Guy Katz, Clarke Barrett, D. Dill, K. Julian, and M. Kochenderfer. Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks. In CAV, 2017.

The lifecycle of neural network verification

Property

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Property

Training

DL2
ACT
etc.

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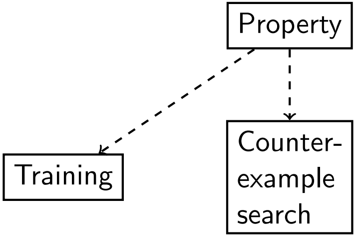

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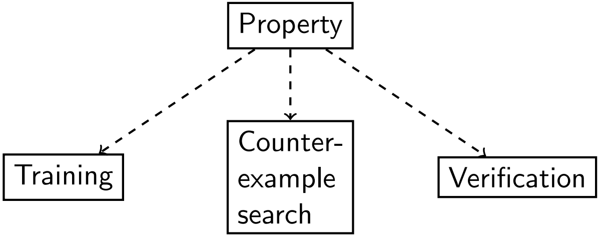

DL2
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PGD
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etc.

Marabou
Eran
etc.

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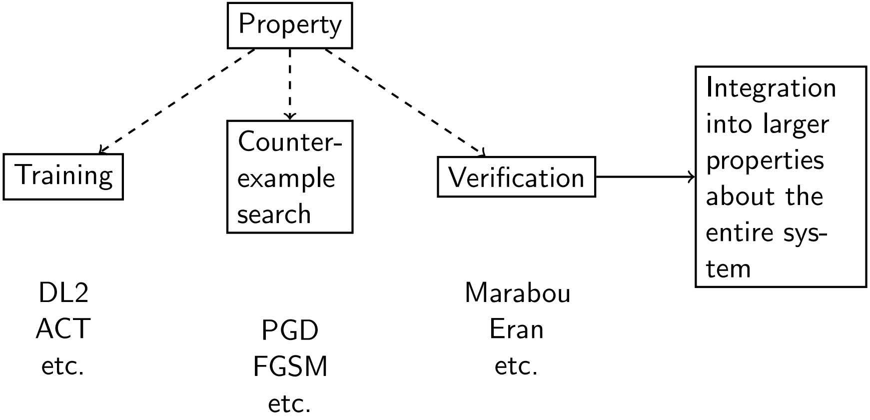

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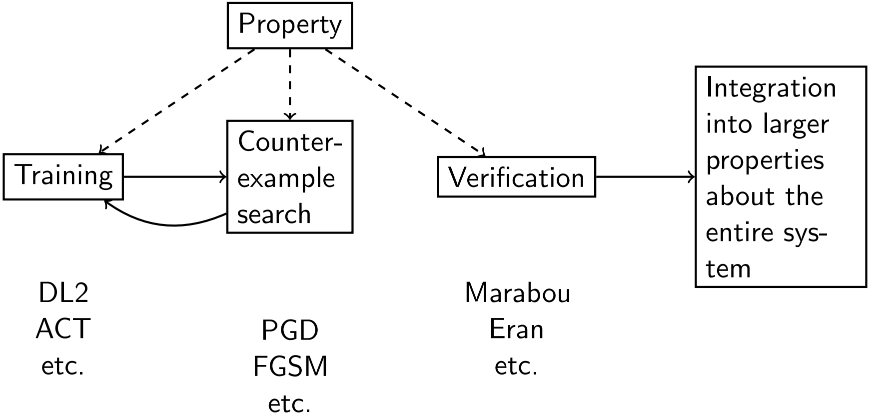

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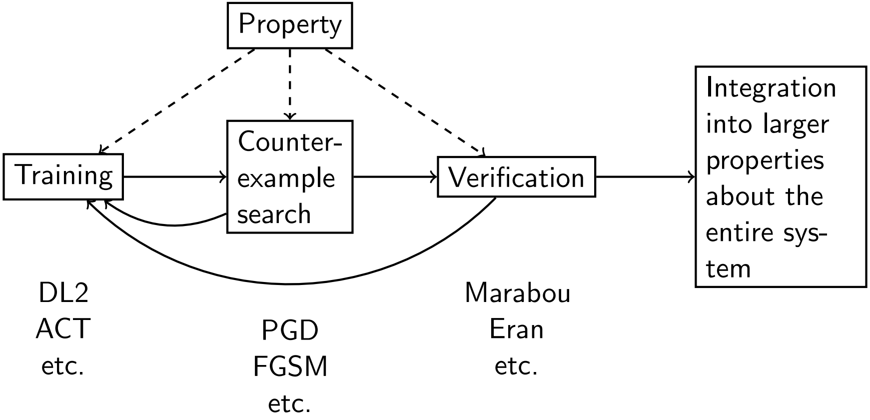

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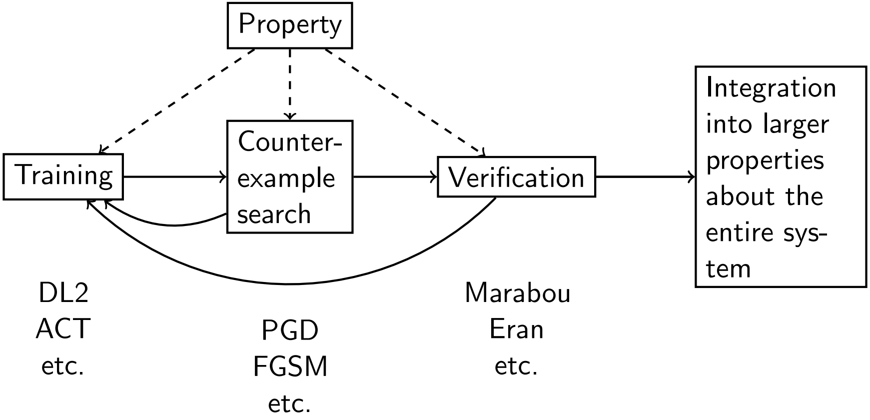

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- ML: understanding and integrating property-driven training
- Programming: finding the right languages to support these developments
- Complex systems: integration of neural net verification into complex systems

Some of these problems are aggravated by insufficient programming language or API support

Lets look under the hood...

Training framework: DL2

```python
class RobustnessConstraint(Constraint):


    def get_domains(self, x_batches, y_batches):
        assert len(x_batches) == 1
        n_batch = x_batches[0].size()[0]

        return [[Box(np.clip(x_batches[0][i].cpu().numpy() - self.eps, 0, 1),
                     np.clip(x_batches[0][i].cpu().numpy() + self.eps, 0, 1))
                for i in range(n_batch)]]

    def get_condition(self, z_inp, z_out, x_batches, y_batches):
        n_batch = x_batches[0].size()[0]
        z_out = transform_network_output(z_out, self.network_output)[0]
        #z_logits = F.log_softmax(z_out[0], dim=1)

        pred = z_out[np.arange(n_batch), y_batches[0]]

        limit = torch.FloatTensor([0.3])
        if self.use_cuda:
            limit = limit.cuda()
        return dl2.GEQ(pred, torch.log(limit))
```

Fischer, M., Balunovic, M., Drachsler-Cohen, D., Gehr, T., Zhang, C., and Vechev, M. T. DL2: training and querying neural networks with logic. In Proc. of the 36th Int. Conf. Machine Learning, ICML 2019

Training framework: ART

```
    @classmethod
    def property6a(cls, dom: AbsDom):
        p = AcasProp(name='property6a', dom=dom, safe_fn='cols_is_min', viol_fn='cols_not_min',
                     fn_args=[AcasOut.CLEAR_OF_CONFLICT])
        p.set_input_bound(AcasIn.RHO, new_low=12000, new_high=62000)
        p.set_input_bound(AcasIn.THETA, new_low=0.7, new_high=3.141592)
        p.set_input_bound(AcasIn.PSI, new_low=-3.141592, new_high=-3.141592 + 0.005)
        p.set_input_bound(AcasIn.V_OWN, new_low=100, new_high=1200)
        p.set_input_bound(AcasIn.V_INT, new_low=0, new_high=1200)
        p.set_all_applicable_as(False)
        p.set_applicable(1, 1, True)
        return p
```

Lin, X., Zhu, H., Samanta, R., and Jagannathan, S. (2020). Art: Abstraction refinement-guided training for provably correct neural networks. In FMCAD 2020

Verification framework: Marabou


```python
def test_acas_1_1_normalize():
    """
    Test the 1,1 experimental ACAS Xu network.
    By passing "normalize=true" to read_nnet, Marabou adjusts the parameters of the first and last layers of the
      network to incorporate the normalization.
    As a result, properties can be defined in the original input/output spaces without any manual normalization.
    """
    filename =  "acasxu/ACASXU_experimental_v2a_1_1.nnet"
    testInputs = [
        [1000.0, 0.0, -1.5, 100.0, 100.0],
        [10000.0, -3.0, -1.5, 300.0, 300.0],
        [5000.0, -3.0, 0.0, 300.0, 600.0]
    ]
    testOutputs = [
        [177.87553729, 173.75796115, 193.05920806, 153.07876146, 195.00495022],
        [-0.55188079, 0.46863711, 0.44250383, 0.44151988, 0.43959133],
        [29.9190734, 27.2386958, 45.02497222, 14.5610455, 46.86448056]
    ]
    network = evaluateFile(filename, testInputs, testOutputs, normalize = True)
```

Katz, G., Huang, D. A., Ibeling, D., Julian, K., Lazarus, C., Lim, R., Shah, P., Thakoor, S., Wu, H., Zeljic, A., Dill, D. L., Kochenderfer, M. J., and Barrett, C. W. (2019). The Marabou framework for verification and analysis of deep neural networks. In CAV 2019

Verification framework: ERAN

```
[12000, 62000]
[0.7, 3.141592][-3.141592, -0.7]
[-3.141592, -3.136592]
[100, 1200]
[0, 600]
```

```
5
y0 min
```

Singh, G., Gehr, T., Püschel, M., and Vechev, M. T. (2019). An abstract domain for certifying neural networks. PACMPL, 3(POPL):41:1–41:30.

Verification property language: VNNLIB

```
(assert (or
    (and (<= X_0 0.700434925) (>= X_0 -0.129289109)
         (<= X_1 0.499999896) (>= X_1 0.11140846)
         (<= X_2 -0.499204121) (>= X_2 -0.499999896)
         (<= X_3 0.5) (>= X_3 -0.5)
         (<= X_4 0.5) (>= X_4 -0.5))
    (and (<= X_0 0.700434925) (>= X_0 -0.129289109)
         (<= X_1 -0.11140846) (>= X_1 -0.499999896)
         (<= X_2 -0.499204121) (>= X_2 -0.499999896)
         (<= X_3 0.5) (>= X_3 -0.5)
         (<= X_4 0.5) (>= X_4 -0.5))
))

; unsafe if coc is not minimal
(assert (or
    (and (<= Y_1 Y_0))
    (and (<= Y_2 Y_0))
    (and (<= Y_3 Y_0))
    (and (<= Y_4 Y_0))
```

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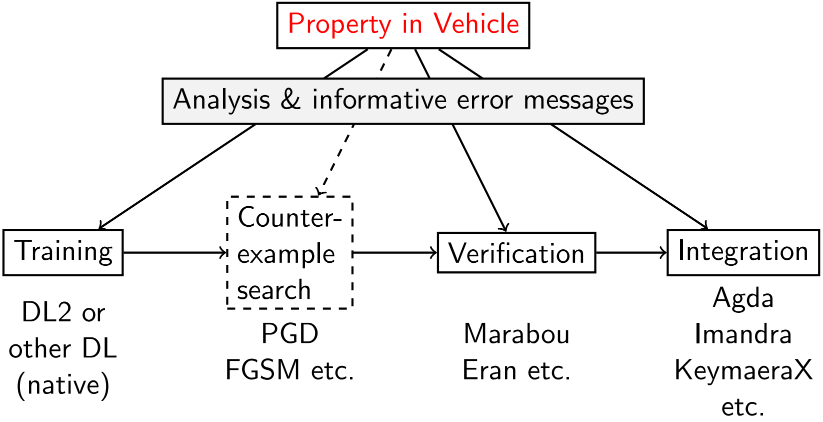
- I^P Interpretability – code is not easy to understand.
- $I^\int$ Integration – properties of networks cannot be linked to larger control system properties.
- E^G Embedding gap – little support for translation between problem space (as in original spec) and input space (at neural network level).

Vehicle is designed to address all of these problems

Vehicle ...

is a domain-specific functional language for writing high-level property specifications for neural networks



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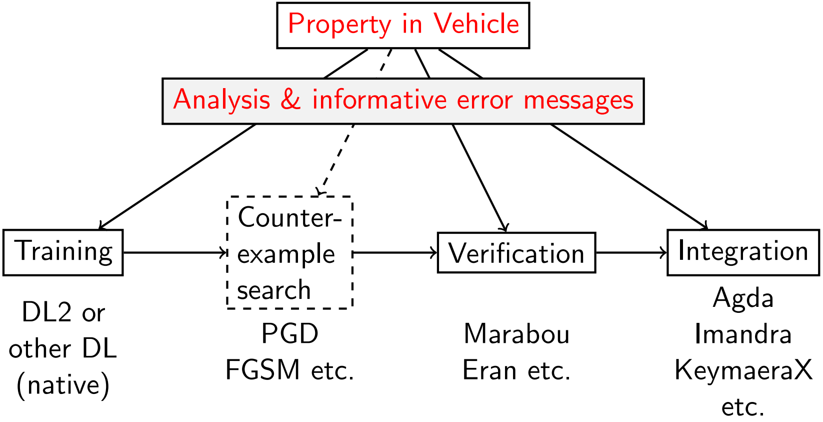

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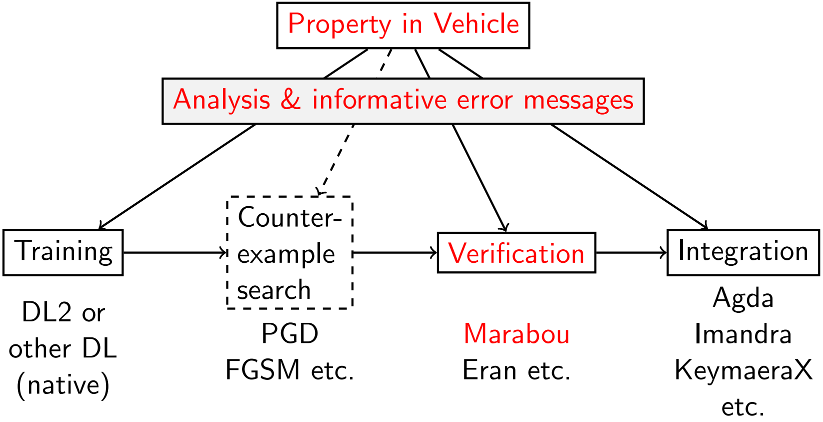

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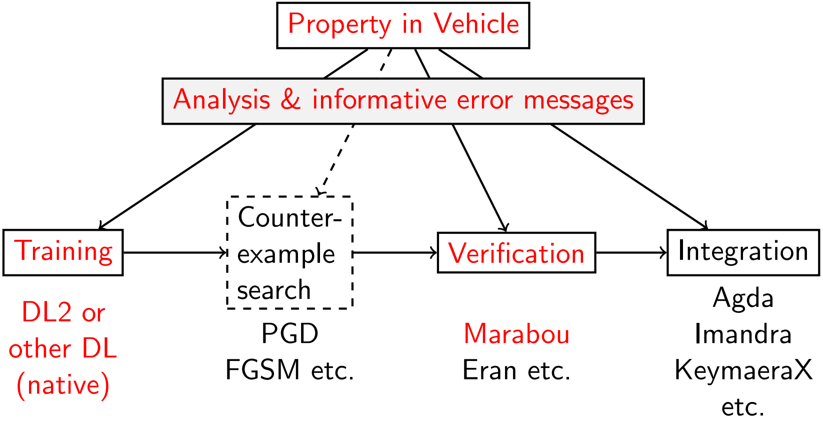

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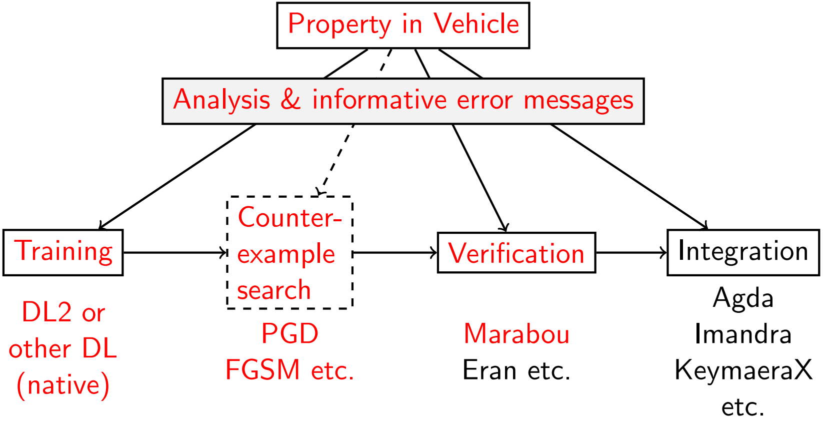

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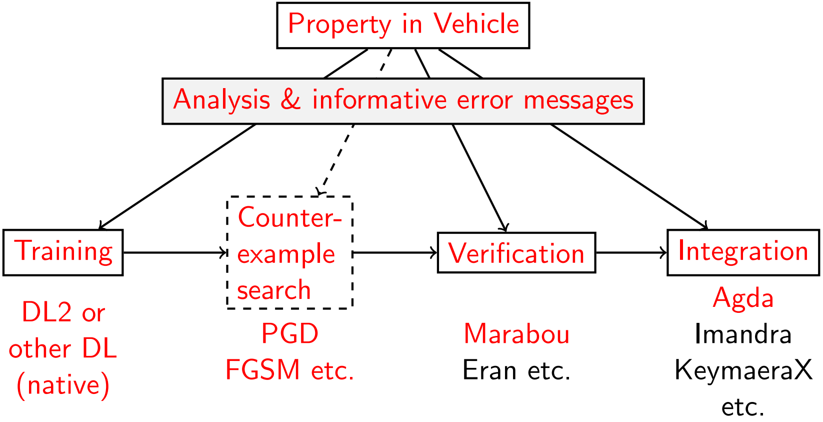

Other Similar APIs

- Socrates [in Python]: Given a spec and a network (in JSON), calls different NN verifiers.

  L. H. Pham, J. Li, and J. Sun. 2020. SOCRATES: Towards a Unified Platform for Neural Network Verification. CoRR abs/2007.11206.

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- CoCoNet [in Python]: NN format converter with GUI

  D. Guidotti, A. Tacchella, L. Pulina, S. Demarchi 2023. `http://neuralverification.org/`

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- NeVer 2.0 [in Python]: added training, prunning and quantization to this functionality.

  D. Guidotti, L. Pulina, and A. Tacchella. 2020. NeVer 2.0: Learning, Verification and Repair of Deep Neural Networks. CoRR abs/2011.09933.

  Resolved: I^O (partially). Left untesolved: I^P, $I^\int$, E^G

- CoCoNet [in Python]: NN format converter with GUI

  D. Guidotti, A. Tacchella, L. Pulina, S. Demarchi 2023. `http://neuralverification.org/`

  Resolved: I^P (partially). Left untesolved: I^O, $I^\int$, E^G

- Caisar [in OCAML] – general specification language and connection to several NN Verifiers

  J. Girard-Satabin, M. Alberti, F. Bobot, Z. Chihani, and A. Lemesle. 2022. CAISAR: A platform for Characterizing Artificial Intelligence Safety and Robustness. In AISafety.

  Resolved: I^P, $I^\int$. Left unresolved: I^O, E^G

Vehicle's Aim...

... is to resolve the problems I^O, I^P, $I^\int$, E^G

Vehicle's Aim...

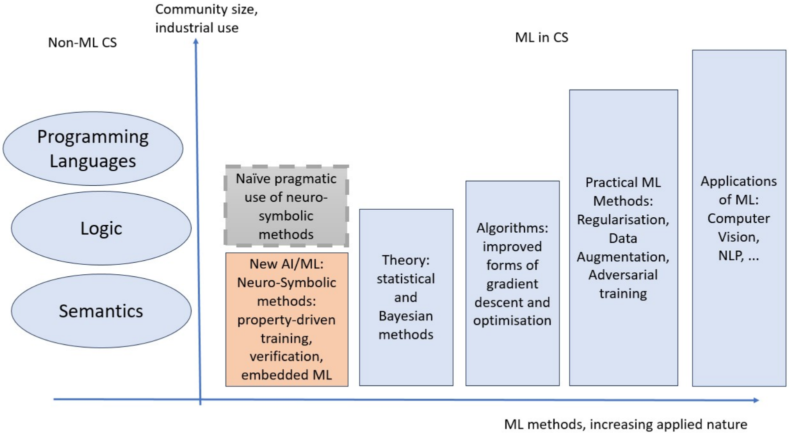
... is to resolve the problems I^O, I^P, $I^\int$, E^G

... and support community's effort towards resolution of the "Grand Challenges"

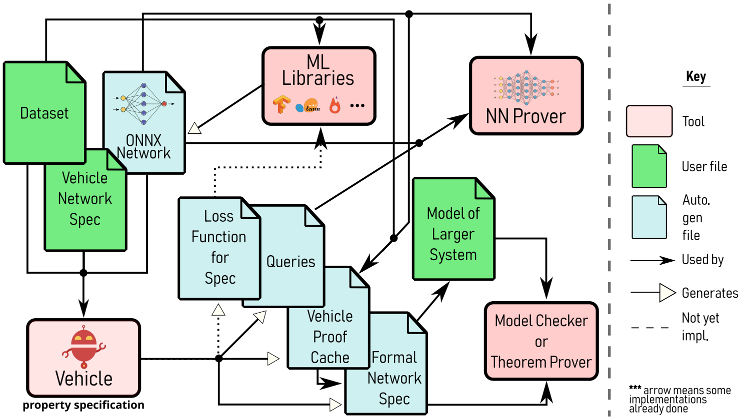
"Grand Challenges" & **Vehicle**

- Theory: finding appropriate verification properties
- Solvers: undecidability of non-linear real arithmetic and scalability of neural network verifiers
- ML: understanding and integrating property-driven training
- Programming: finding the right languages to support these developments
- Complex systems: integration of neural net verification into complex systems

Vehicle among other disciplines



Vehicle Architecture



Sources

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- N. Slusarz, E. Komendantskaya, M. Daggitt, R. Stewart, K. Stark: Logic of Differentiable Logics: Towards a Uniform Semantics of DL. LPAR 2023.
- Matthew L. Daggitt, Wen Kokke, Robert Atkey, Luca Arnaboldi, Ekaterina Komendantskaya: Vehicle: Interfacing Neural Network Verifiers with Interactive Theorem Provers. FOMLAS 2022
- Vehicle Team: The Vehicle language: `https://github.com/vehicle-lang` 2023.
- M.Daggitt and W.Kokke: Vehicle User Manual. `https://vehicle-lang.readthedocs.io` 2023.
- The Vehicle team: Vehicle Tutorial `https://vehicle-lang.github.io`. 2023. Tutorial code repository `https://github.com/vehicle-lang/vehicle-tutorial`.

Purpose of this Tutorial...

- Discuss challenges in NN verification ("grand" and technical)
- Understand how logic and PL semantics can contribute in this domain
- Introduce **Vehicle** specification language at the user level
- Give you a bit of practice with NN verification and gather feedback

Plan for the rest of this tutorial

- Before coffee break:
  - Brief introduction to **Vehicle** specification language
  - Neural Network Robustness: an iconic verification case
- During and after the break:
  - Exercise session: write and verify a **Vehicle** spec
    Tutorial pages: `https://vehicle-lang.github.io`
    Join tutorial Slack channel via the tutorial page, to ask questions
- After the break:
  - Property-driven training in Vehicle
  - Large system integration
  - Application areas for NN Verification