Neural Network Verification with Vehicle

Today's presentors: Ekaterina Komendantskaya and Luca Arnaboldi (live), Matthew Daggitt (online), on behalf of the Vehicle team

The Vehicle Team

Matthew Daggitt

Natalia Slusarz

Ben Coke

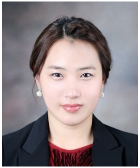
Wen Kokke

Luca Arnaboldi

Marco Casadio

Bob Atkey

Katya K



Jeonghyeon Lee

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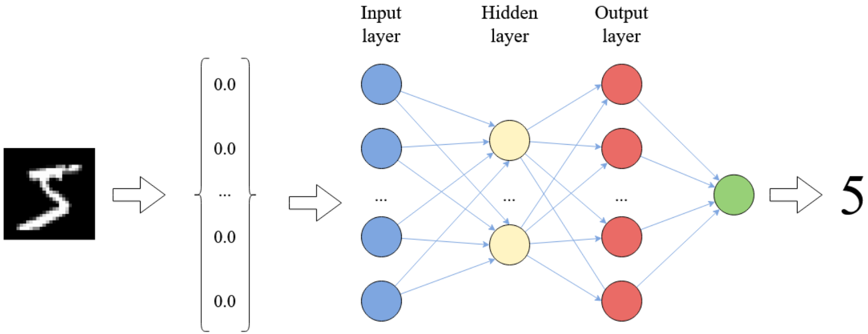
Neural nets for classification



Formally,

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

Neural networks

... are ideal for "perception" tasks:

- approximate functions when exact solution is hard to get
- tolerant to noisy and incomplete data

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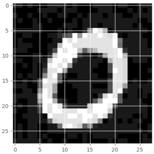
  - adversarial attacks
  - data poisoning
  - catastrophic forgetting

One example: Adversarial Attacks



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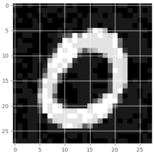

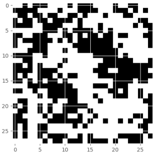

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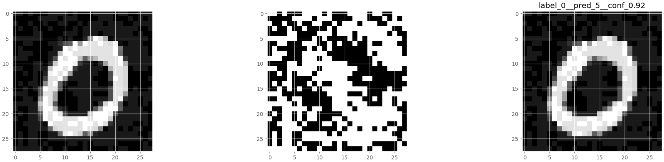

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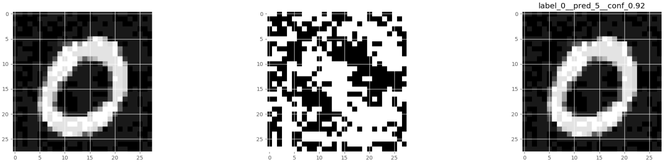

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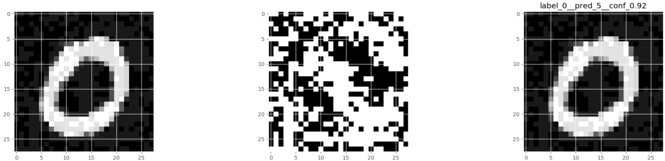
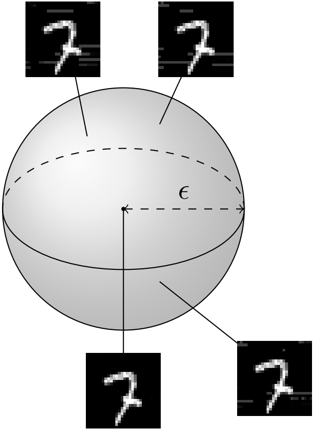


the perturbations are imperceptible to human eye

attacks transfer from one neural network to another

affect any domain where neural networks are applied

Verification Property: "ϵ-ball robustness"



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

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

Another example property: ACAS Xu

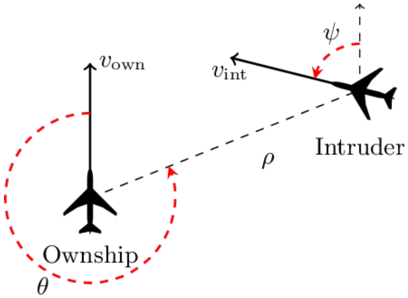
A collision avoidance system for unmanned autonomous aircraft.

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



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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.

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

More Generally

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

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

First NN Verification Tool Pulina and Tacchella (2011)

First Adversarial Attack Baggio et al (2013)

Panda Gibbon Paper Szegedy et al. (2013)

First Acoustic Adversarial Attack Vaidya et al (2015)

Notion of Adversarial Robustness Fawzi A. (2015)

What tools are available?
2015

approximate **adverserial** **complete** **others**

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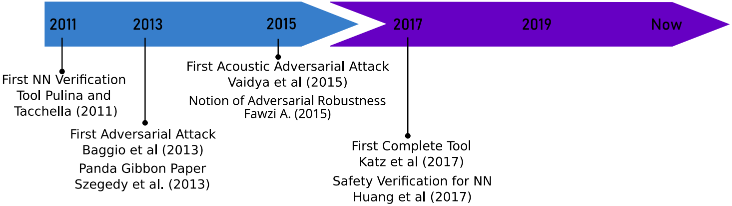

What tools are available?

2017

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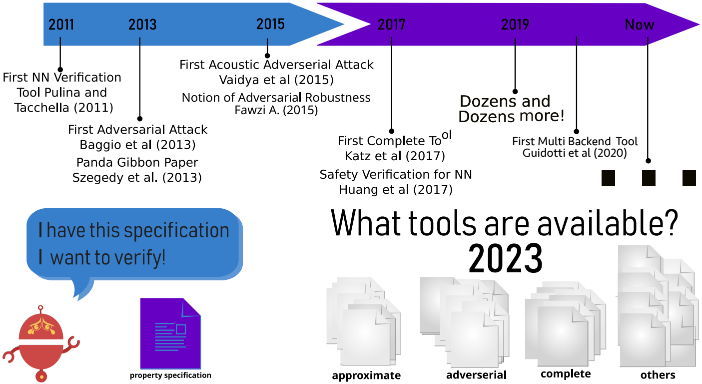

Current Verifier Landscape

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

International Standards and Competitions

https://www.vnnlib.org/

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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.

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The lifecycle of neural network verification

Property

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Property

Training

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DL2
ACT
etc.

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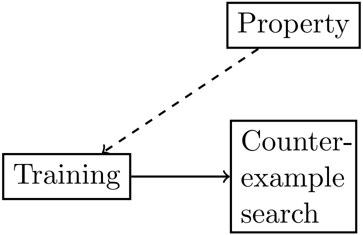

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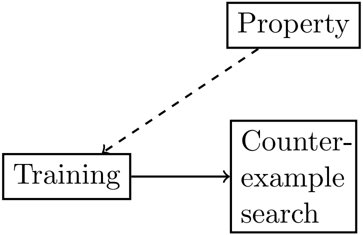

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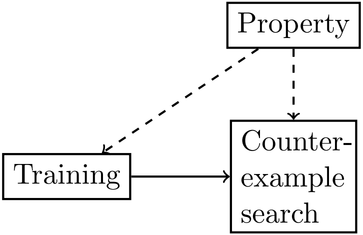

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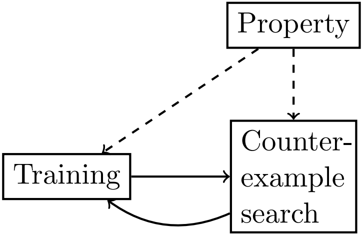

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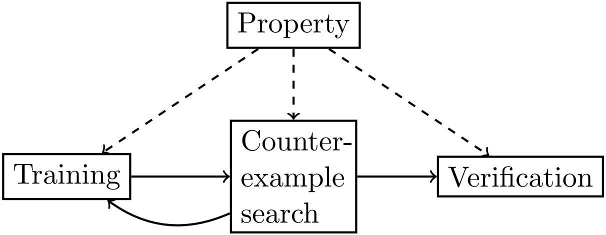

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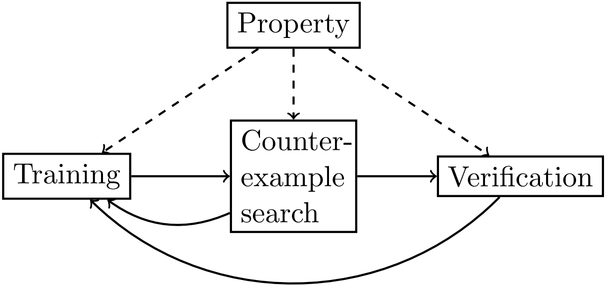

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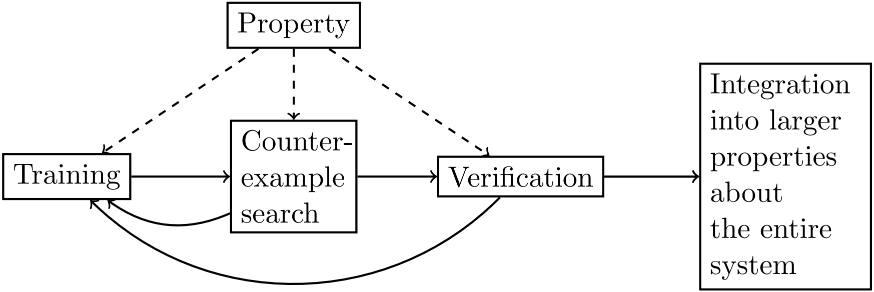

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Challenges the area faces

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- 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

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

Lets look under the hood...

Training framework: DL2

```
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

```python
    @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))
))
```

Recap: What are the problems from the PL perspective?

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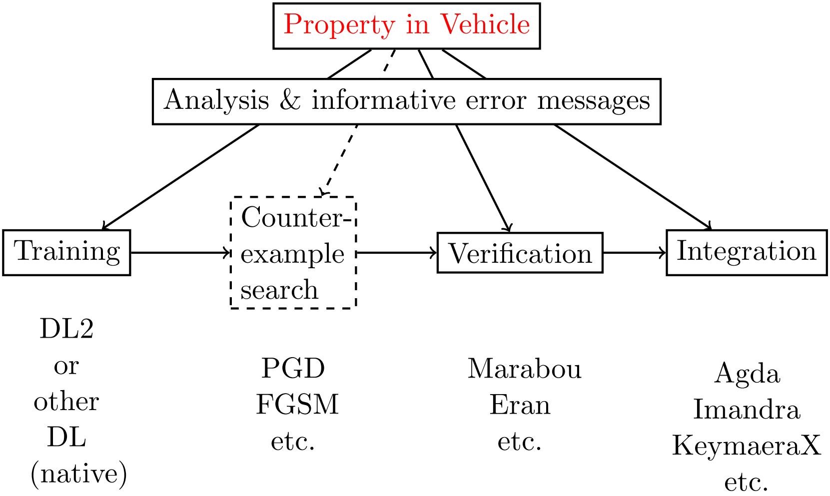
- I^P Interpretability – code is not easy to understand.
- $I^\int$ Integration – properties of networks cannot be linked to larger control system properties.
- E^G Embedding gap – little support for translation between problem space (as in original spec) and input space (at neural network level).

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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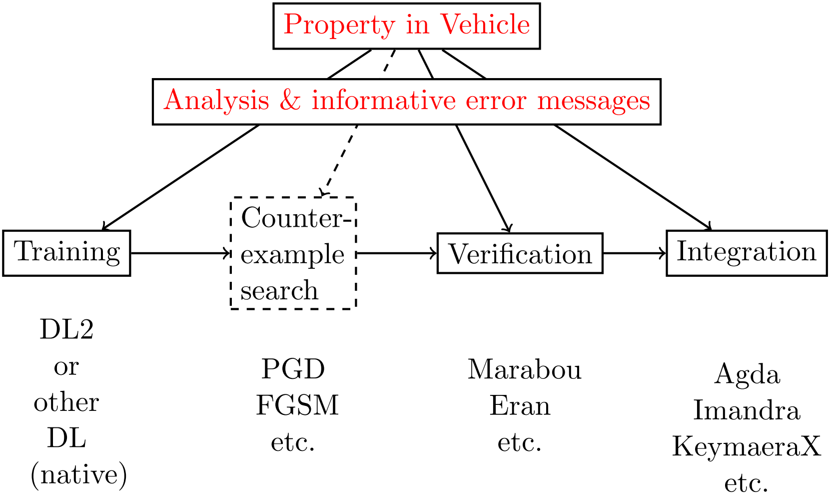

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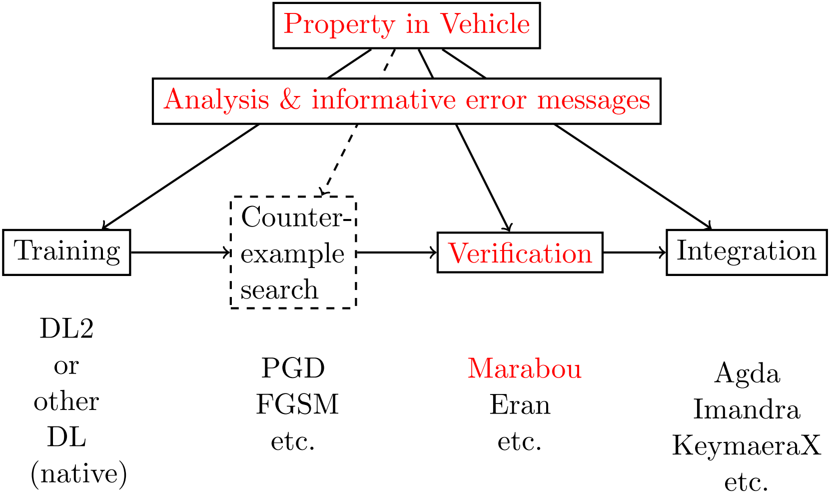

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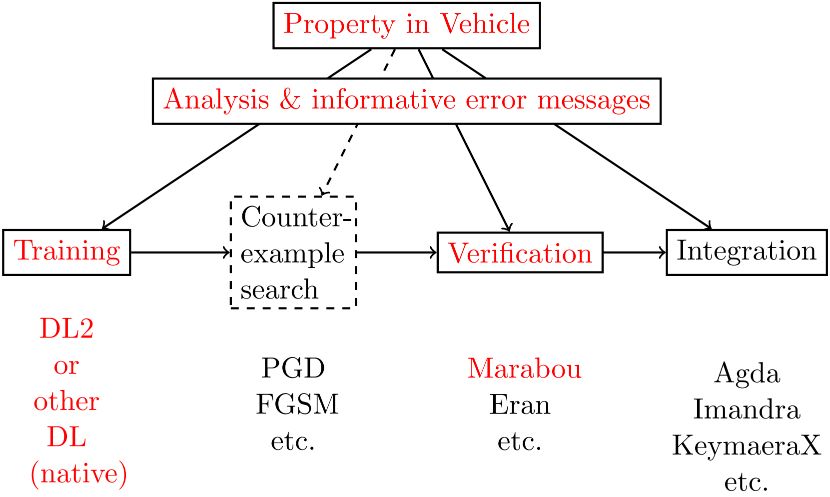

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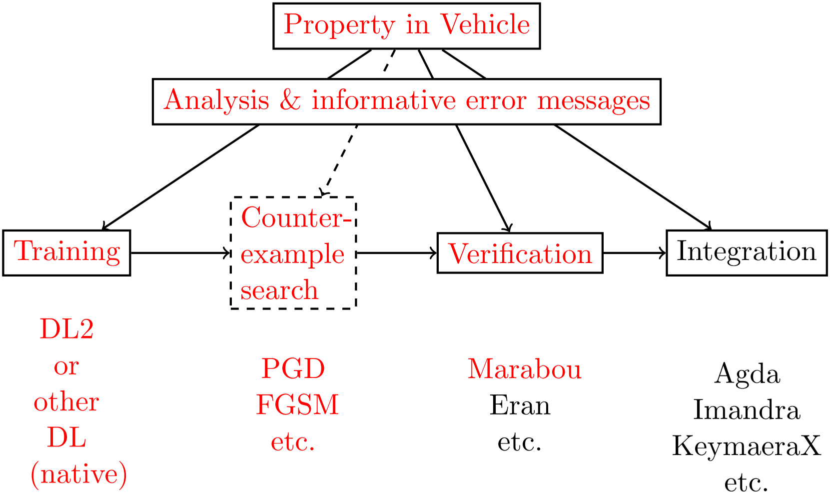

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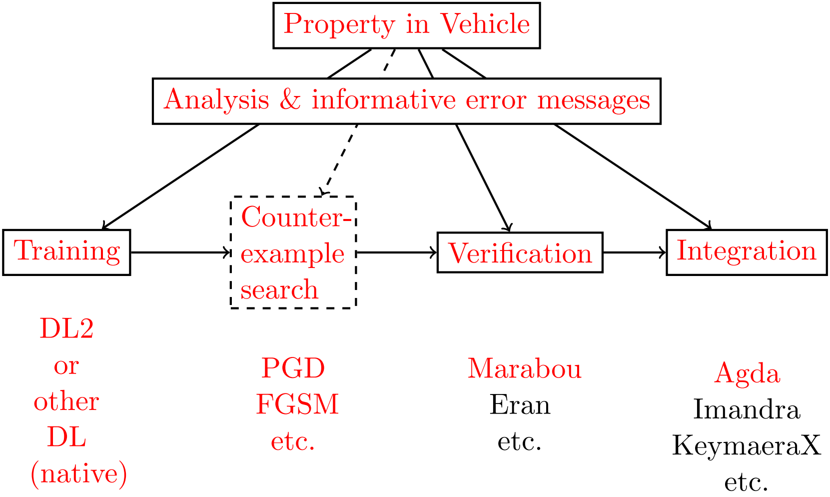

Other Similar APIs

- 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.

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

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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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- 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.

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

“Grand Challenges” & **Vehicle**

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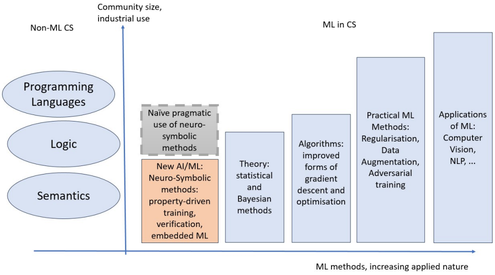
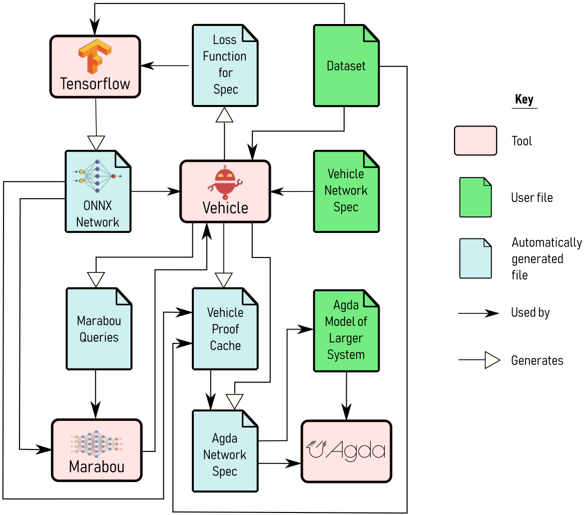
- ML: understanding and integrating property-driven training
- Programming: finding the right languages to support these developments
- Complex systems: integration of neural net verification into complex systems



Vehicle Architecture



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- 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.
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Purpose of this Tutorial...

- Introduce **Vehicle** specification language at the user level
- Discuss challenges in NN verification (”grand” and technical)
- 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:
  - Poperty-driven training: theory and demo in Vehicle
  - Application areas for NN Verifiction and large system integration