# Neural Network Verification With Vehicle: Chapter 1 - Introduction

## ICFP'23 Tutorial

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# The Vehicle Team


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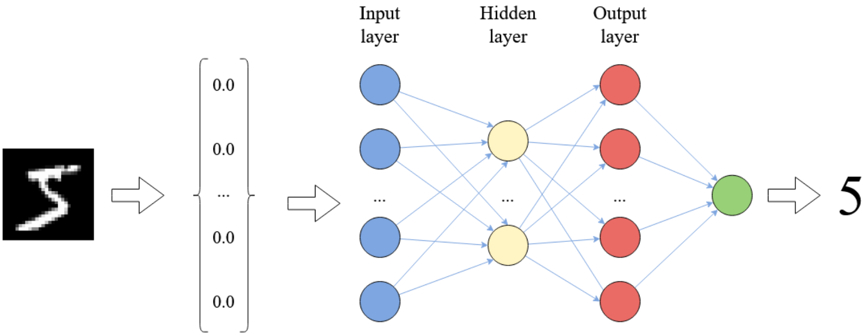
Marco Casadio


Katya K

# Neural nets for classification




Formally,

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

# Neural networks

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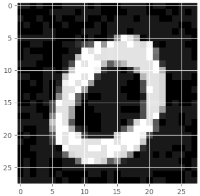
  adversarial attacks
  data poisoning
  catastrophic forgetting

# One example: Adversarial Attacks



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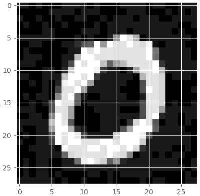


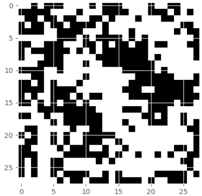

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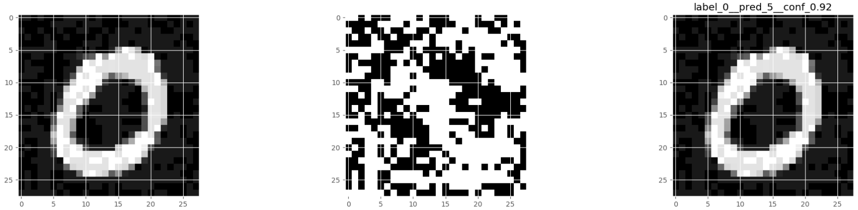

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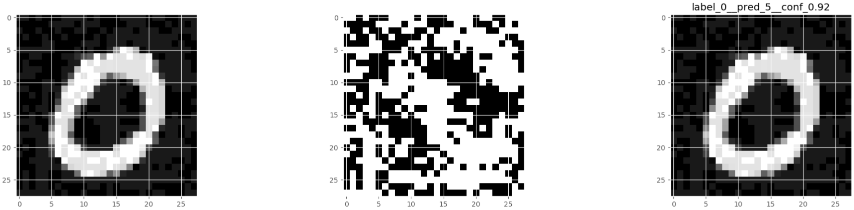


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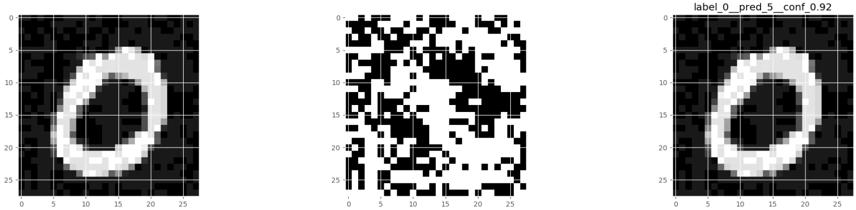


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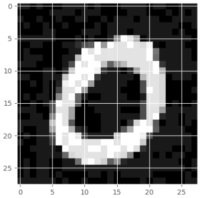
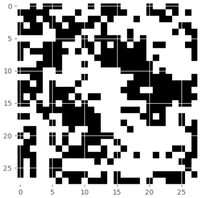
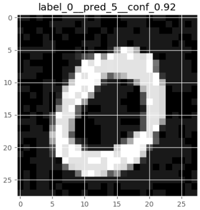
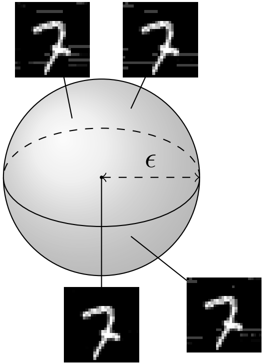







- the perturbations are imperceptible to human eye
- attacks transfer from one neural network to another
- affect any domain where neural networks are applied

# Verification Property: "$\epsilon$-ball robustness"




An $\epsilon$-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, $\rho$
- Angle to intruder, $\theta$
- Intruder heading, $\varphi$
- 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.

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

# 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

First NN Verification Tool Pulina and Tacchella (2011)

First Adversarial Attack Baggio et al (2013)

Panda Gibbon Paper Szegedy et al. (2013)

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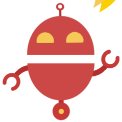
Notion of Adversarial Robustness Fawzi A. (2015)

I have this specification I want to verify!



property specification

## What tools are available?
## 2015

approximate

adverserial

complete

others

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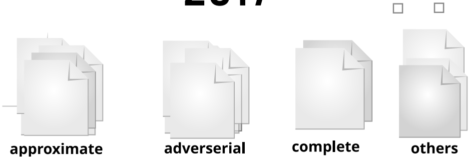
## 2017



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2019 — Dozens and Dozens more!

First Multi Backend Tool Guidotti et al (2020)

Now ...

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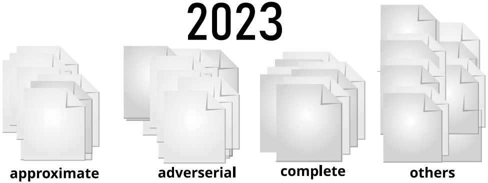
property specification

What tools are available?

2023



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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

$\boxed{\text{Property}}$

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Property

Training

DL2
ACT
etc.

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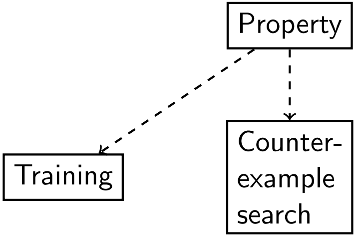


DL2
ACT
etc.

PGD
FGSM
etc.

# The lifecycle of neural network verification

Property

| Training | Counter-example search | Verification |
| --- | --- | --- |
| DL2<br>ACT<br>etc. | PGD<br>FGSM<br>etc. | Marabou<br>Eran<br>etc. |

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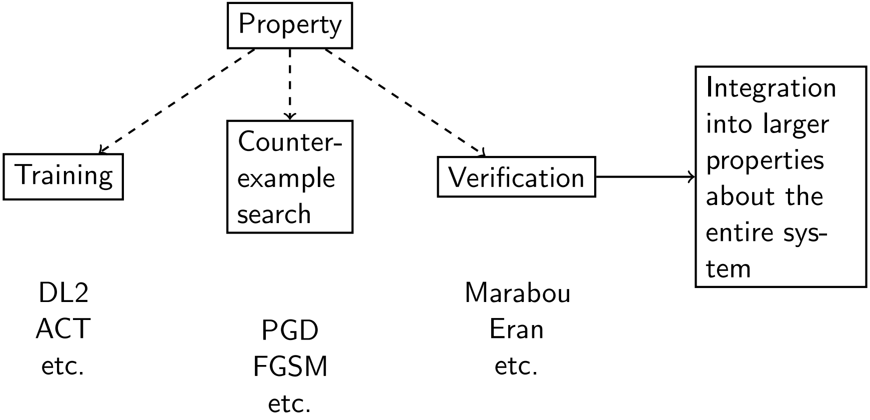

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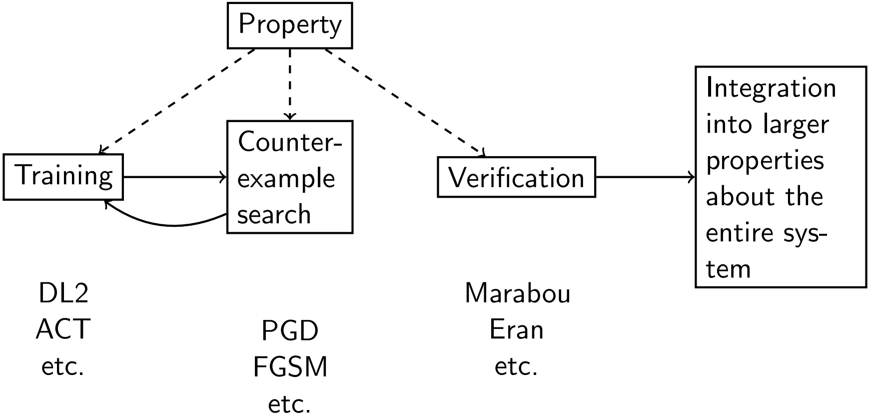

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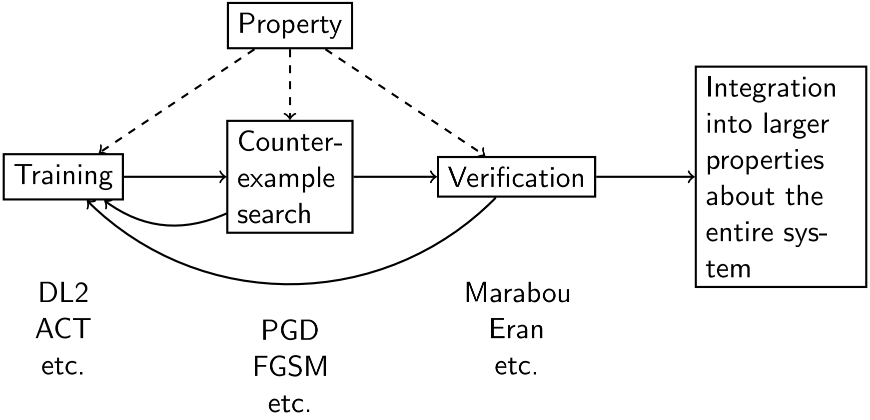

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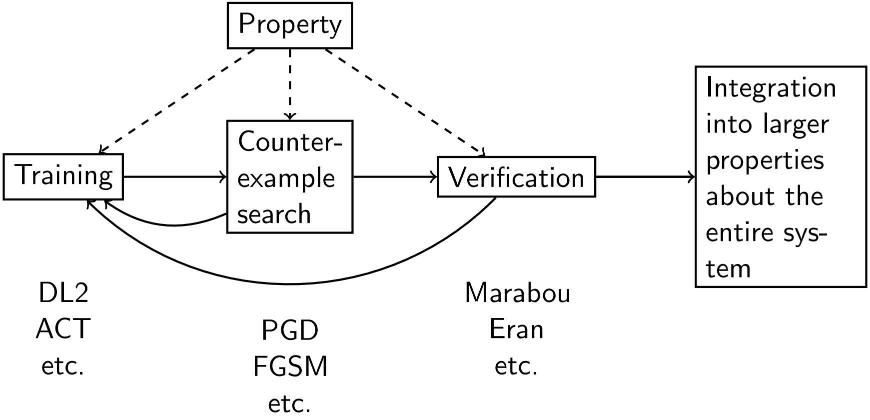

# Challenges the area faces



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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



```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



```
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)
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         (<= 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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- $I^O$ Interoperability – properties are not portable between training/counter-example search/ verification.
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- $I^\int$ Integration – properties of networks cannot be linked to larger control system properties.

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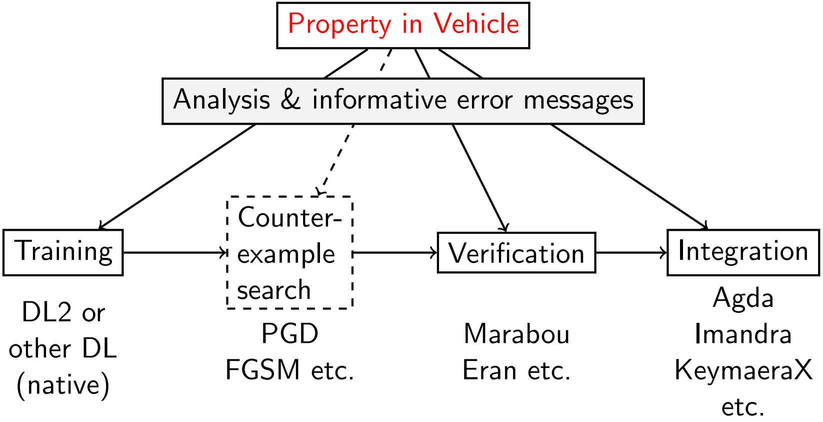
- $I^O$ Interoperability – properties are not portable between training/counter-example search/ verification.
- $I^P$ Interpretability – code is not easy to understand.
- $I^{\int}$ Integration – properties of networks cannot be linked to larger control system properties.
- $E^G$ Embedding gap – little 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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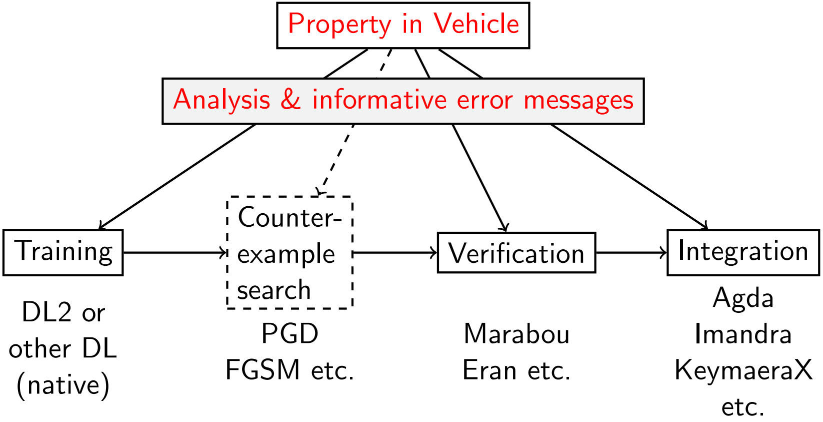

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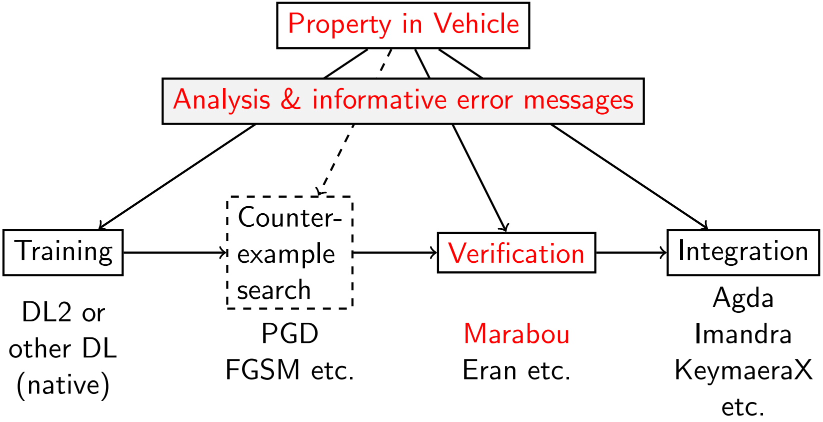

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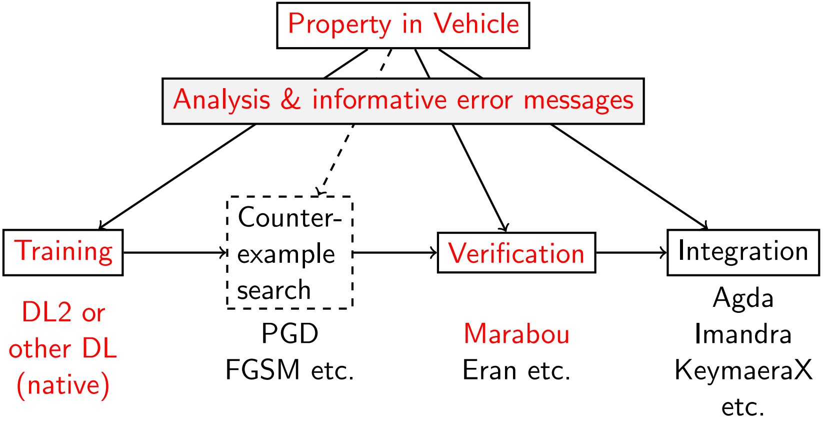

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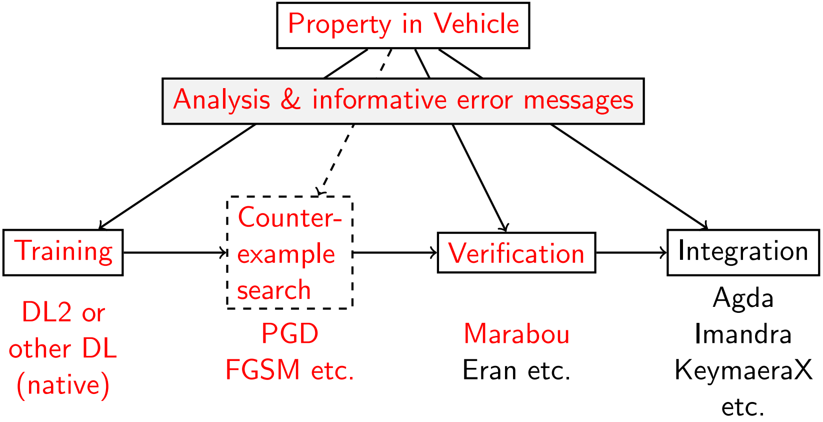

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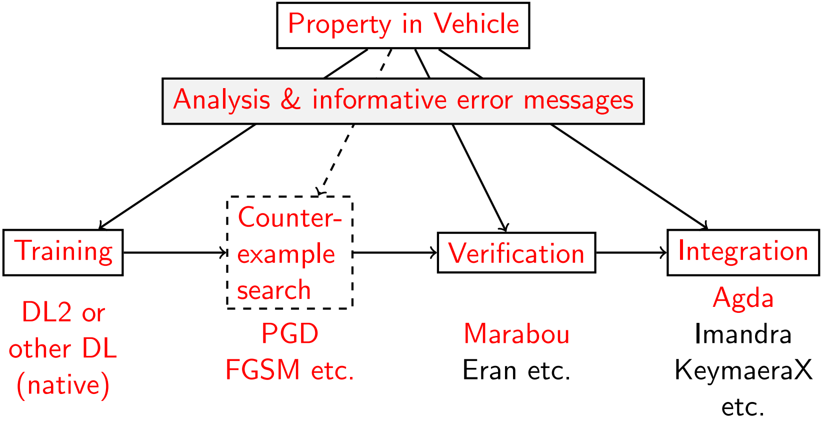

# Other Similar APIs



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

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

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  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"

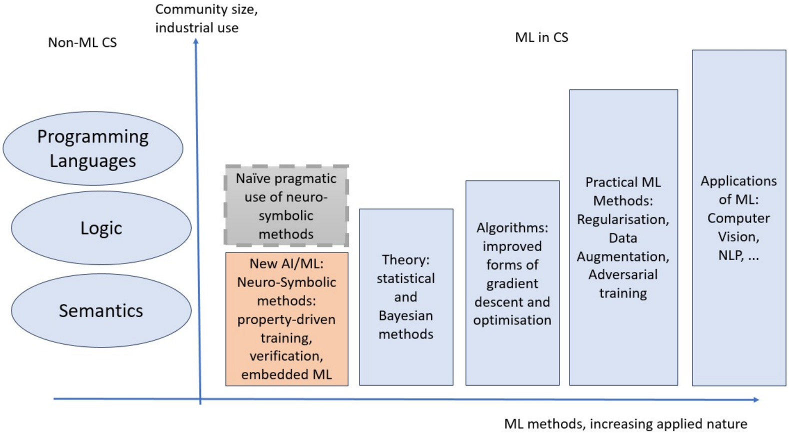
# “Grand Challenges” & **Vehicle**



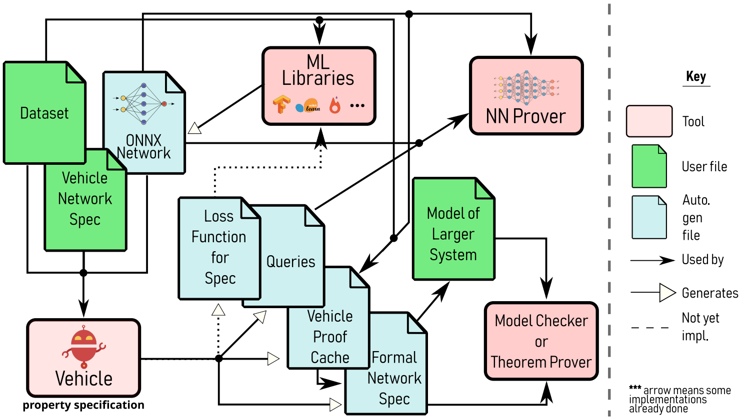
- Theory: finding appropriate verification properties
- Solvers: undecidability of non-linear real arithmetic and scalability of neural network verifiers
- ML: understanding and integrating property-driven training
- Programming: finding the right languages to support these developments
- Complex systems: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