Neural Network Verification with Vehicle

Ekaterina Komendantskaya and Matthew Daggitt (today's presenters), on behalf of the Vehicle team

The Vehicle Team

Matthew Daggitt

Rob Stewart

Natalia Slusarz

Wen Kokke

Luca Arnaboldi

Kathrin Stark

Bob Atkey

Marco Casadio

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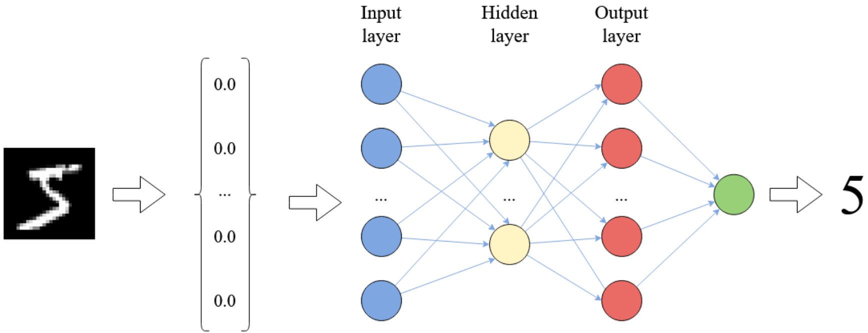
Neural nets for classification



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
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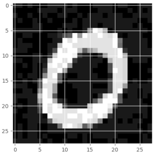
  adversarial attacks
  data poisoning
  catastrophic forgetting

One example: Adversarial Attacks



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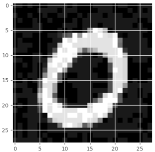

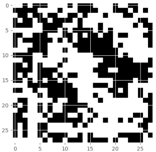

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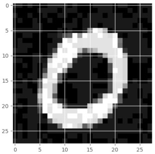

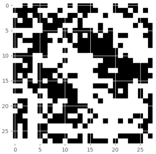

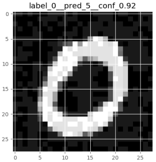

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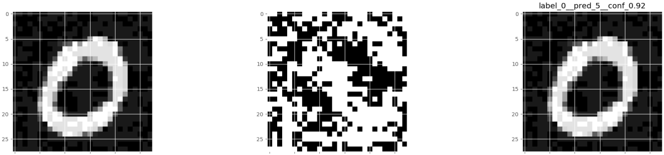

the perturbations are imperceptible to human eye

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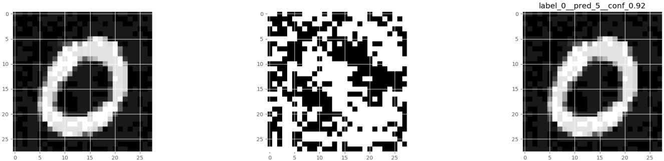

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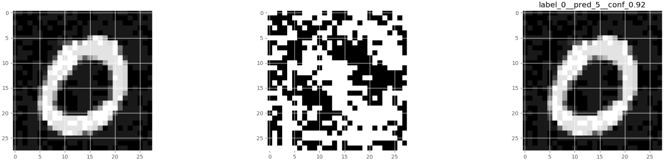

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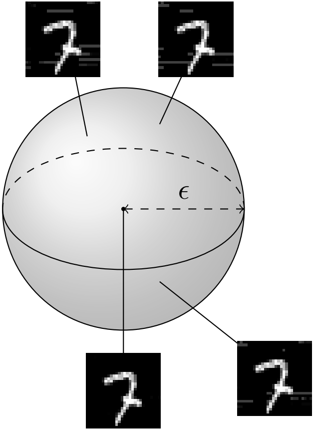
attacks transfer from one neural network to another

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

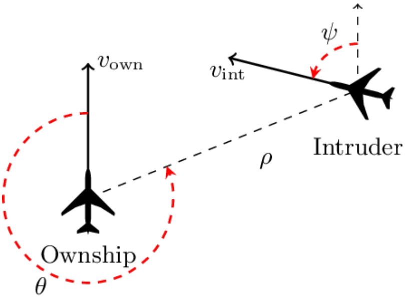
A collision avoidance system for unmanned autonomous aircraft.

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)

<u>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.</u>

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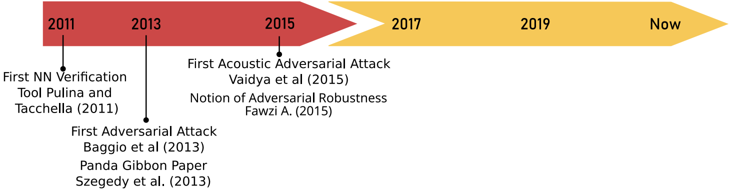
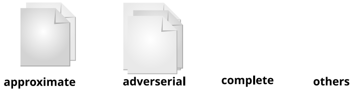
Casadio, M., Komendantskaya, E., Daggitt, M.L., Kokke, W., Katz, G., Amir, G., Refaeli, I.: Neural network robustness as a verification property: A principled case study. In: Computer Aided Verification (CAV 2022).

Overview of The Verification Landscape



What tools are available?
2015



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)

First Complete Tool Katz et al (2017)

Safety Verification for NN Huang et al (2017)

What tools are available?

2017

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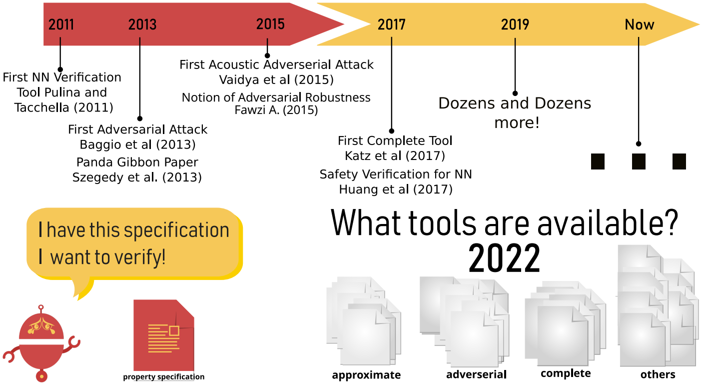

Current Verifier Landscape

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

International Standards and Competitions

https://www.vnnlib.org/

Current Verifier Landscape

A whole range of domain-specific verifiers exist:

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- ...

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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

$\boxed{\text{Property}}$

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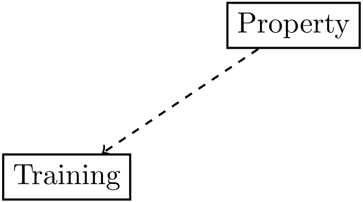
Property

Training

The lifecycle of neural network verification



DL2
ACT
etc.

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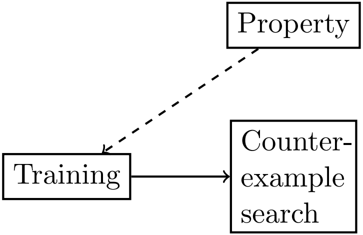

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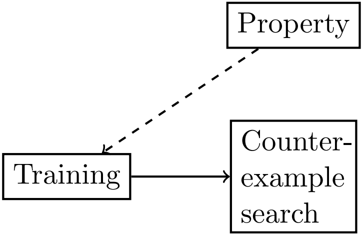

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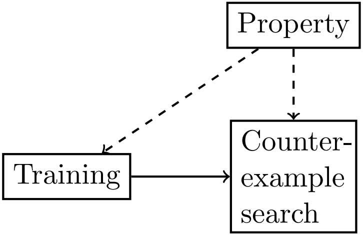

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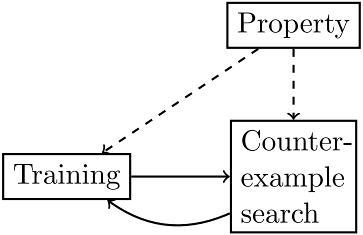

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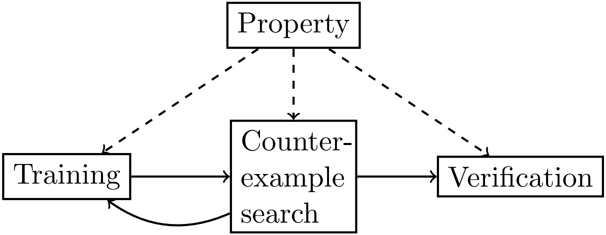

DL2	PGD	Marabou
ACT	FGSM	Eran
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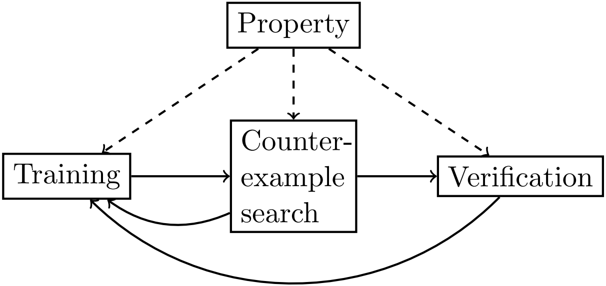

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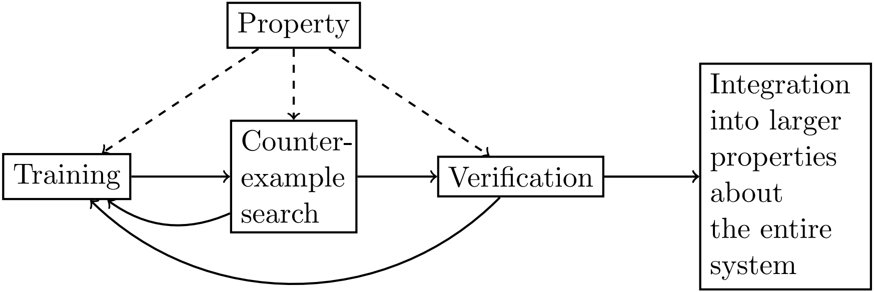

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Challenges the area faces

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- 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

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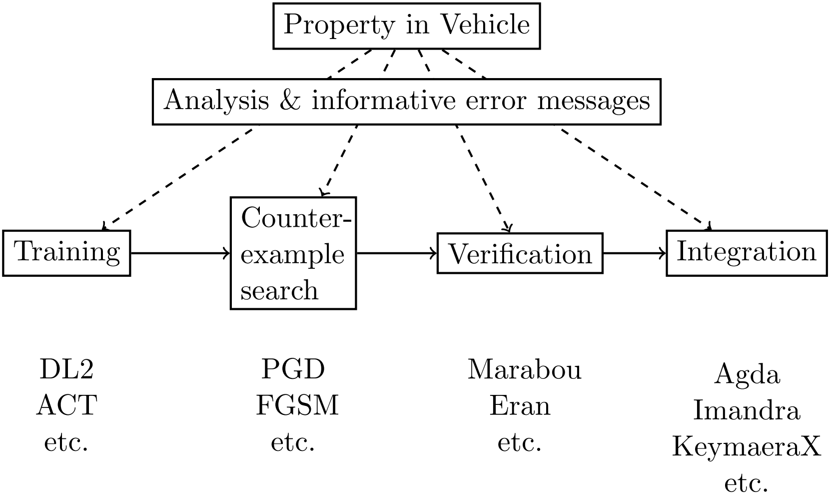
- I^O Interoperability – properties are not portable between training/counter-example search/ verification.
- I^P Interpretability – code is not easy to understand.
- $I^\int$ Integration – properties of networks cannot be linked to larger control system properties.
- E^G Embedding gap – little support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



Other Similar APIs

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

  Long H. Pham, Jiaying Li, and Jun Sun. 2020. SOCRATES: Towards a Unified Platform for Neural Network Verification. CoRR abs/2007.11206 (2020).

  Cons: I^O, I^P, $I^\int$, E^G

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

  Julien Girard-Satabin, Michele Alberti, François Bobot, Zakaria Chihani, and Augustin Lemesle. 2022. CAISAR: A platform for Characterizing Artificial Intelligence Safety and Robustness. In AISafety (CEUR-Workshop Proceedings). Vienne, Austria.

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Vehicle's Aim...

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

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

Which challenges Vehicle addresses

- Theory: finding appropriate verification properties
- Solvers: undecidability of non-linear real arithmetic and scalability of neural network verifiers
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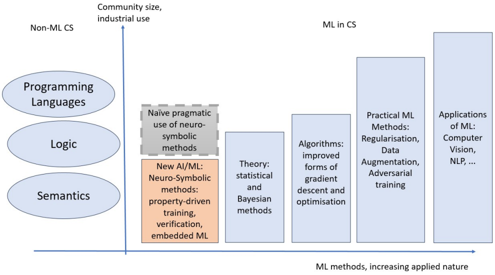
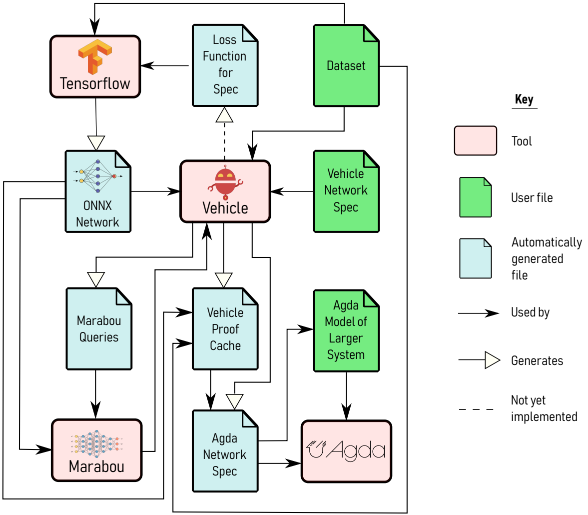
- Complex systems: integration of neural net verification into complex systems



Vehicle Architecture



Sources

- M. Daggitt, R. Atkey, W. Kokke, E. Komendantskaya, L. Arnaboldi: Compiling Higher-Order Specifications to SMT Solvers: How to Deal with Rejection Constructively. CPP 2023
- 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
- Vehicle Team: The Vehicle language: `https://github.com/vehicle-lang` 2023.
- M.Daggitt and W.Kokke: Vehicle User Manual. 2023.

Purpose of this Tutorial...

- Introduce Vehicle specification language at the user level
- Convince FOMLAS audience that it maybe a convenient tool to use (and develop)
- Gather feedback and obtain community support

Thanks

... to Marabou team and FOMLAS organisers for the continuing support!