



Neural Network Verification with Vehicle

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

The Vehicle Team



Matthew Daggitt



Natalia Slusarz



Ben Coke



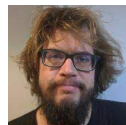
Wen Kokke



Luca Arnaboldi



Marco Casadio



Bob Atkey



Katya
Komendantskaya

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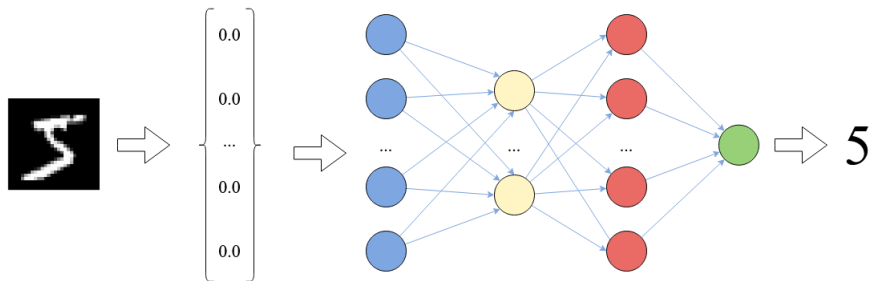
Neural Network Verification: overview of the new domain

The lifecycle of neural network verification

Challenges and Languages

Vehicle's Role and Purpose of this Tutorial

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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BUT

- ▶ solutions not easily conceptualised (**lack of explainability**)
- ▶ prone to a new range of safety and security problems:



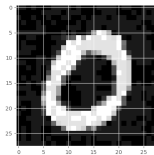
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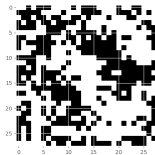
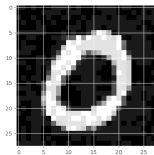
BUT

- ▶ solutions not easily conceptualised (**lack of explainability**)
- ▶ prone to a new range of safety and security problems:
 - adversarial attacks
 - data poisoning
 - catastrophic forgetting

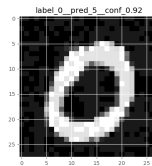
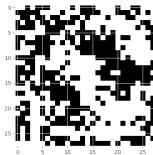
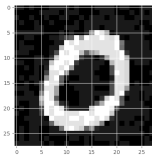
One example: Adversarial Attacks



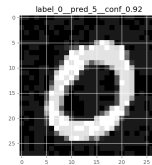
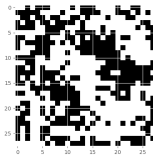
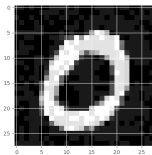
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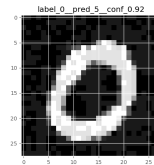
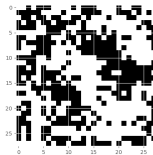
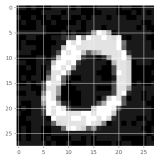


One example: Adversarial Attacks



the perturbations are imperceptible to human eye

One example: Adversarial Attacks



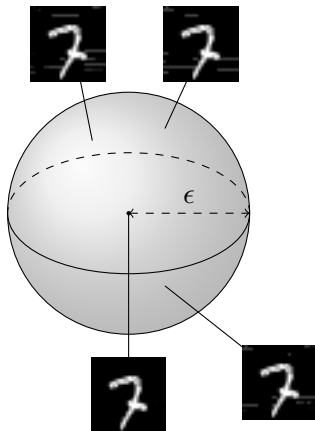
the perturbations are imperceptible to human eye
attacks transfer from one neural network to another

One example: Adversarial Attacks



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



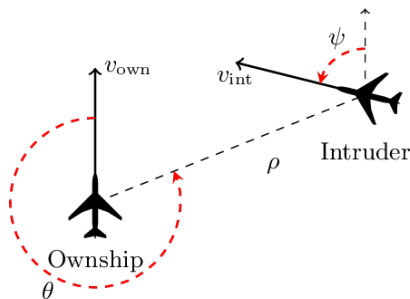
A collision avoidance system for unmanned autonomous aircraft.

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





The system was originally implemented as a 2Gb lookup table but was replaced with a neural network in order to improve size and latency requirements.



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10 different specified properties in total.



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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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10 different specified properties in total.

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.



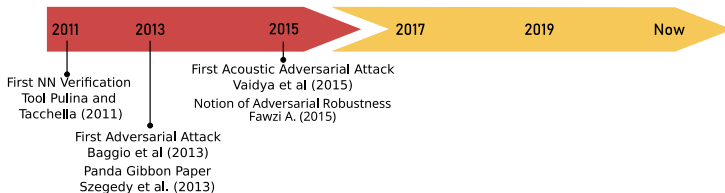
Given $N : R^n \rightarrow R^m$

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



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



I have this specification
I want to verify!



property specification

What tools are available? 2015



approximate

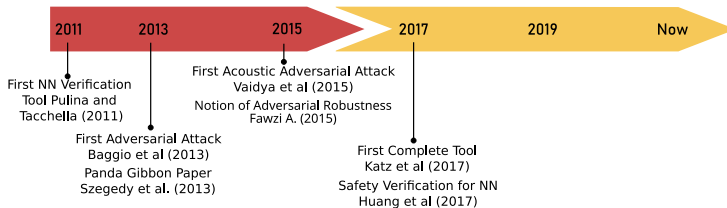


adversarial

complete

others

Overview of The Verification Landscape



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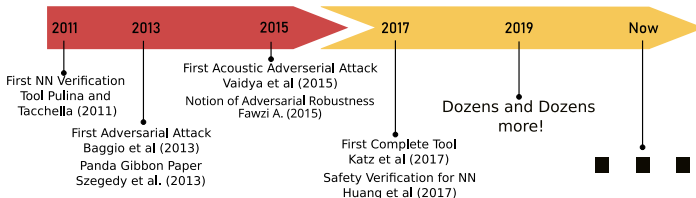


complete



others

Overview of The Verification Landscape



I have this specification
I want to verify!



property specification

What tools are available? 2022



approximate



adversarial



complete



others

Current Verifier Landscape



A whole range of domain-specific verifiers exist:

Current Verifier Landscape



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- ▶ Marabou (SMT technology)

Current Verifier Landscape



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- ▶ ERAN (abstract interpretation + MILP)

Current Verifier Landscape



A whole range of domain-specific verifiers exist:

- ▶ Marabou (SMT technology)
- ▶ ERAN (abstract interpretation + MILP)
- ▶ 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:

- ▶ Marabou (SMT technology)
- ▶ ERAN (abstract interpretation + MILP)
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- ▶ AlphaBetaCROWN (linear bound propagation)
- ▶ ...

International Standards and Competitions

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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

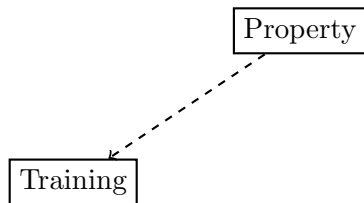
The lifecycle of neural network verification



Property

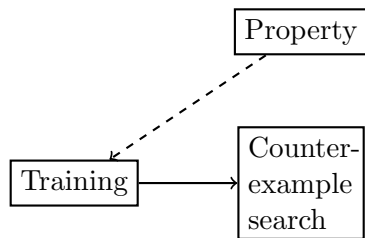
Training

The lifecycle of neural network verification



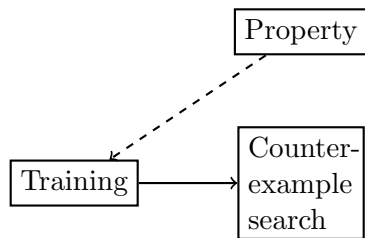
DL2
ACT
etc.

The lifecycle of neural network verification



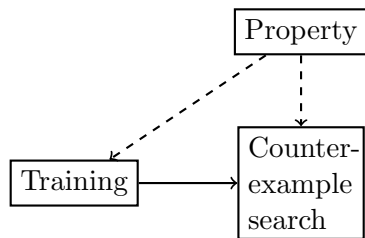
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The lifecycle of neural network verification



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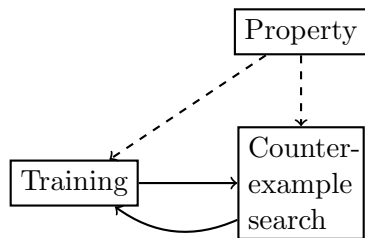
The lifecycle of neural network verification



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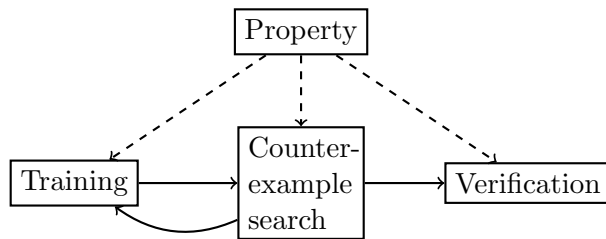
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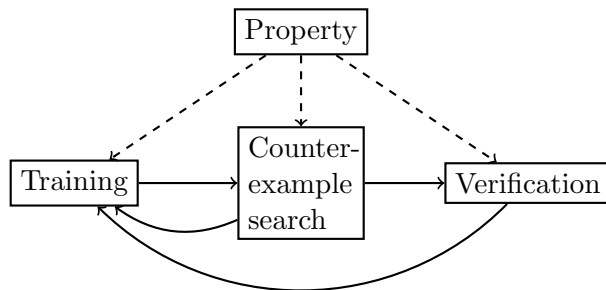


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Marabou
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The lifecycle of neural network verification

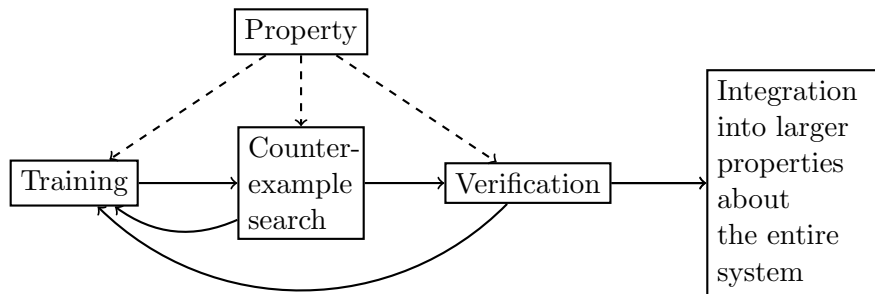


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The lifecycle of neural network verification



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Challenges the area faces



- ▶ Theory: finding appropriate verification properties

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- ▶ 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



```
126 class RobustnessConstraint(Constraint):
127
141     def get_domains(self, x_batches, y_batches):
142         assert len(x_batches) == 1
143         n_batch = x_batches[0].size()[0]
144
145         return [[Box(np.clip(x_batches[0][i].cpu().numpy() - self.eps, 0, 1),
146                        np.clip(x_batches[0][i].cpu().numpy() + self.eps, 0, 1))
147                  for i in range(n_batch)]]
148
149     def get_condition(self, z_inp, z_out, x_batches, y_batches):
150         n_batch = x_batches[0].size()[0]
151         z_out = transform_network_output(z_out, self.network_output)[0]
152         #z_logits = F.log_softmax(z_out[0], dim=1)
153
154         pred = z_out[np.arange(n_batch), y_batches[0]]
155
156         limit = torch.FloatTensor([0.3])
157         if self.use_cuda:
158             limit = limit.cuda()
159         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



```
333     @classmethod
334     def property6a(cls, dom: AbsDom):
335         p = AcasProp(name='property6a', dom=dom, safe_fn='cols_is_min', viol_fn='cols_not_min',
336                     fn_args=[AcasOut.CLEAR_OF_CONFLICT])
337         p.set_input_bound(AcasIn.RHO, new_low=12000, new_high=62000)
338         p.set_input_bound(AcasIn.THETA, new_low=0.7, new_high=3.141592)
339         p.set_input_bound(AcasIn.PSI, new_low=-3.141592, new_high=-3.141592 + 0.005)
340         p.set_input_bound(AcasIn.V_OWN, new_low=100, new_high=1200)
341         p.set_input_bound(AcasIn.V_INT, new_low=0, new_high=1200)
342         p.set_all_applicable_as(False)
343         p.set_applicable(1, 1, True)
344         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



```
1  [12000, 62000]
2  [0.7, 3.141592][-3.141592, -0.7]
3  [-3.141592, -3.136592]
4  [100, 1200]
5  [0, 600]
```

```
1  5
2  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



```
28  (assert (or
29    (and (<= X_0 0.700434925) (>= X_0 -0.129289109)
30      (<= X_1 0.499999896) (>= X_1 0.11140846)
31      (<= X_2 -0.499204121) | (>= X_2 -0.499999896)
32      (<= X_3 0.5) (>= X_3 -0.5)
33      (<= X_4 0.5) (>= X_4 -0.5))
34    (and (<= X_0 0.700434925) (>= X_0 -0.129289109)
35      (<= X_1 -0.11140846) (>= X_1 -0.499999896)
36      (<= X_2 -0.499204121) (>= X_2 -0.499999896)
37      (<= X_3 0.5) (>= X_3 -0.5)
38      (<= X_4 0.5) (>= X_4 -0.5))
39  ))
40
41  ; unsafe if coc is not minimal
42  (assert (or
43    (and (<= Y_1 Y_0))
44    (and (<= Y_2 Y_0))
45    (and (<= Y_3 Y_0))
46    (and (<= Y_4 Y_0))
47  ))
48
```

Recap: What are the problems from the PL perspective?



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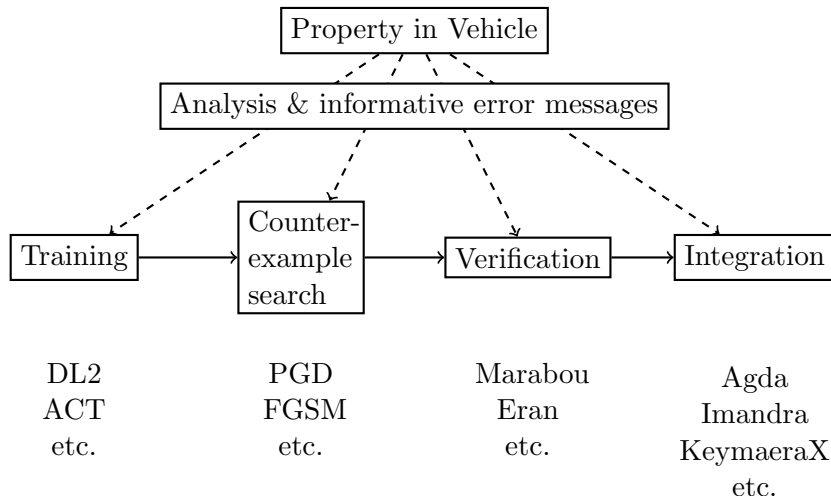


- I^O Interoperability – properties are not portable between training/counter-example search/ verification.
- I^P Interpretability – code is not easy to understand.
- I^f Integration – properties of networks cannot be linked to larger control system properties.
- E^G Embedding gap – little support for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

Left unresolved: I^O , I^P , I^f , E^G

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



Dario Guidotti, Luca Pulina, and Armando Tacchella. 2020. NeVer 2.0: Learning, Verification and Repair of Deep Neural Networks. CoRR abs/2011.09933 (2020).

Resolved: I^O (partially). Left untesolved: I^P , I^f , 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.

Resolved: I^P , I^f . Left unresolved: I^O , E^G

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Vehicle's Aim...



... is to resolve the problems I^O , I^P , I^J , E^G

Vehicle's Aim...



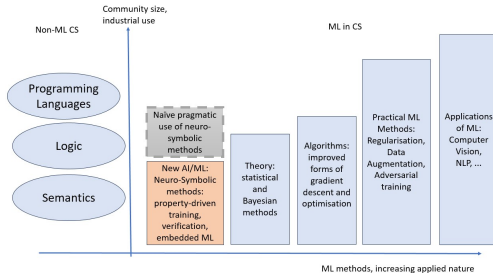
... is to resolve the problems I^O , I^P , I^J , E^G

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

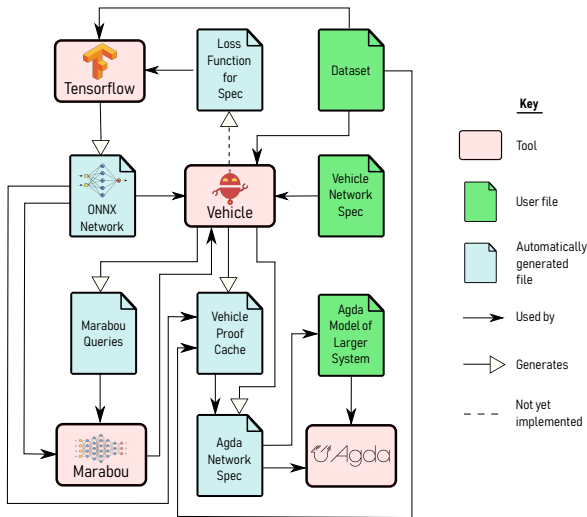
Which of the “Grand Challenges” **Vehicle** addresses



- ▶ 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 Architecture





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!