Vehicle Tutorial Chapter 1: Getting Started

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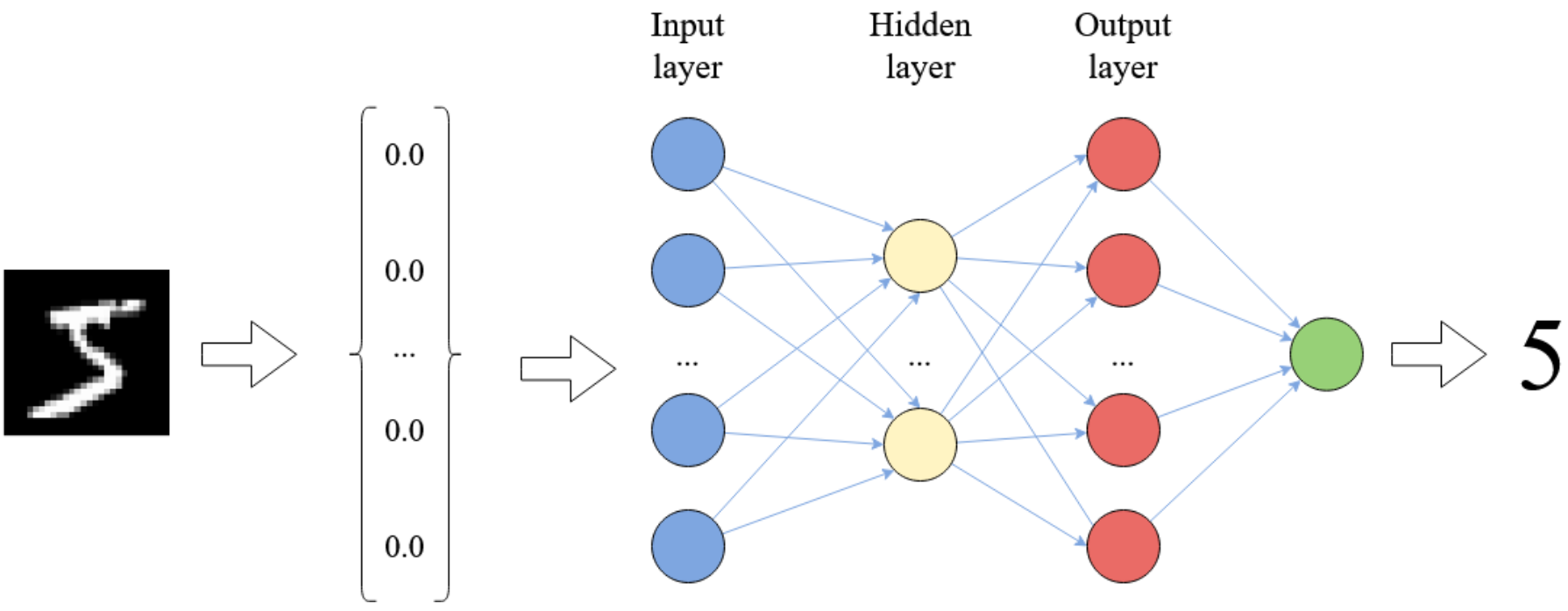
Neural nets for classification



Formally,

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

Neural networks

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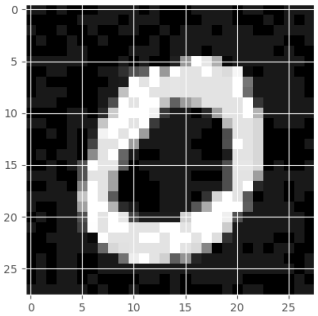
  - adversarial attacks
  - data poisoning
  - catastrophic forgetting

One example: Adversarial Attacks



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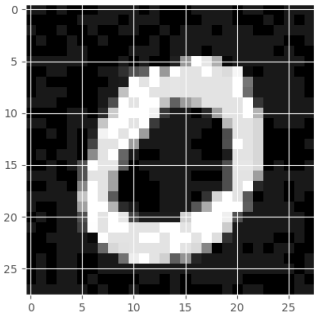

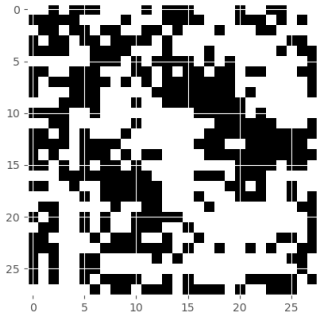

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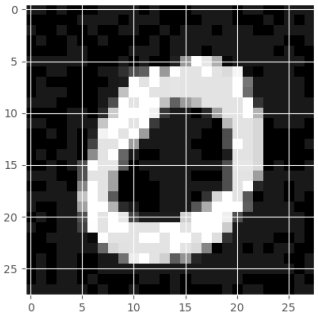

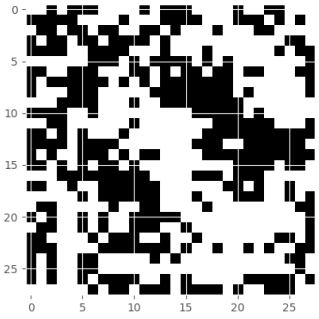

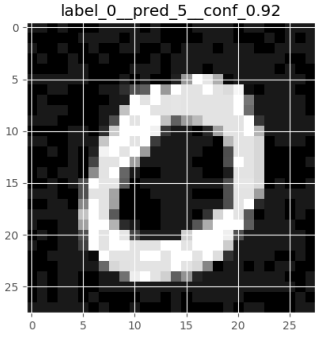

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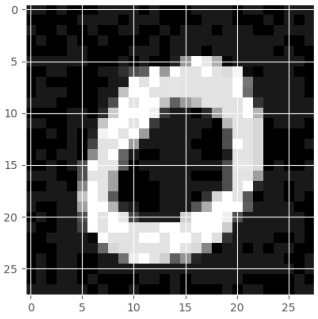

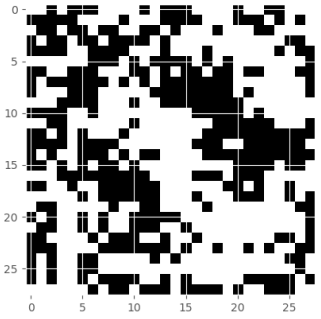

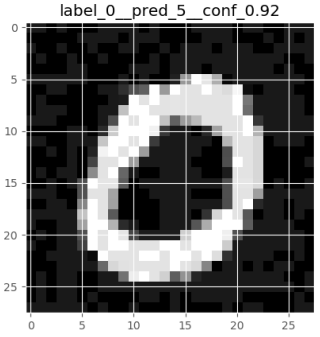

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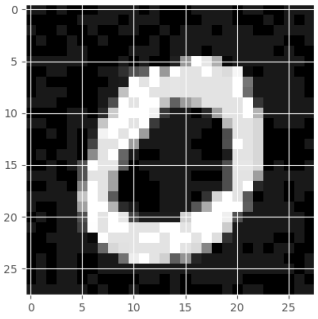

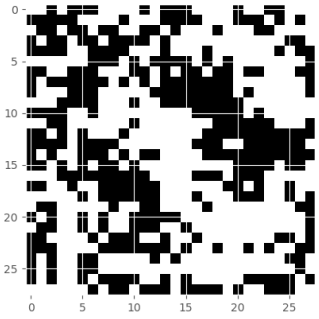

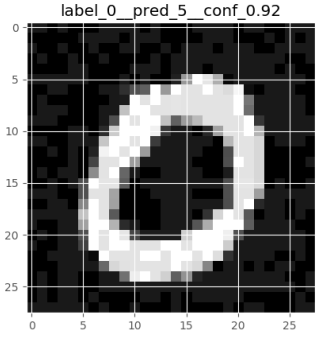

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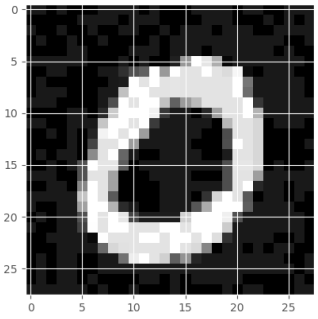

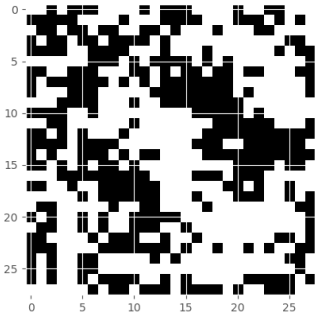

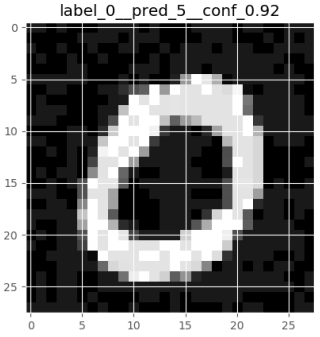

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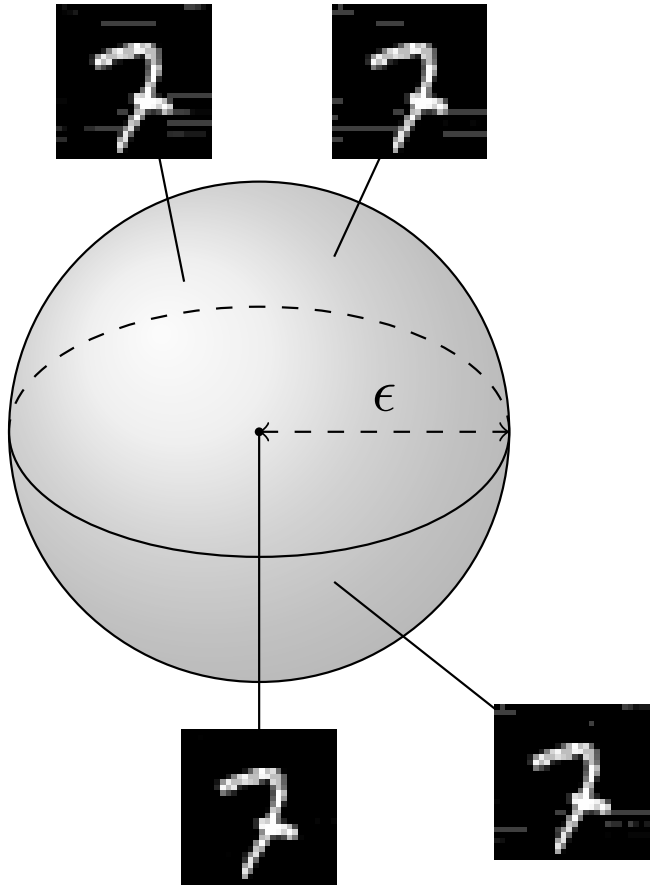
affect any domain where neural networks are applied

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

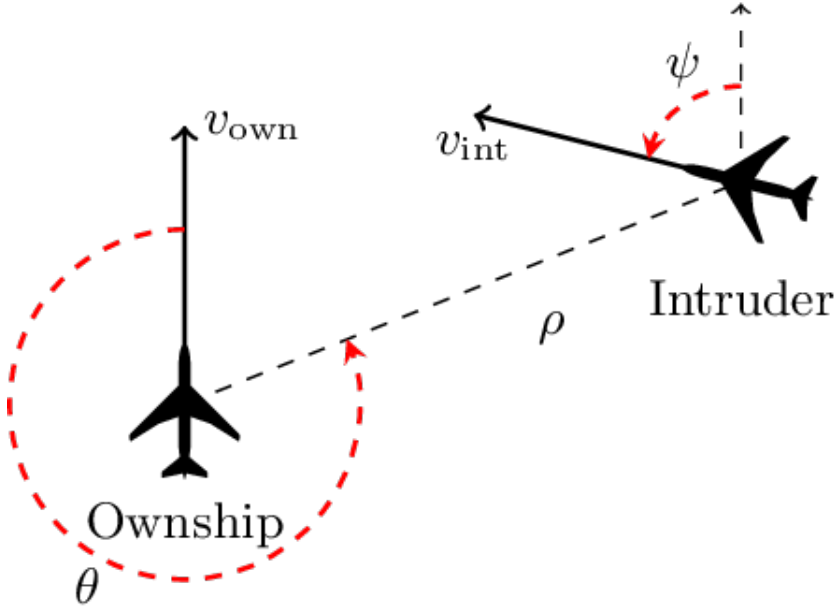
A collision avoidance system for unmanned autonomous aircraft.

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



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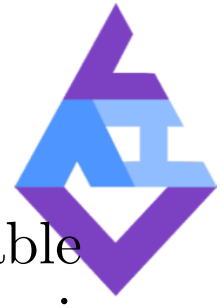

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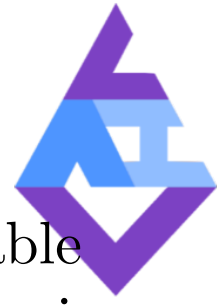

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Definition (ACAS Xu: Property 1)

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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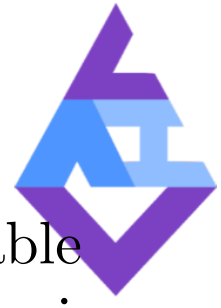

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$$(\rho \geq 55947.691) \wedge (v_{own} \geq 1145) \wedge (v_{int} \leq 60)$$
$$\Rightarrow \text{the score for COC is at most } 1500$$

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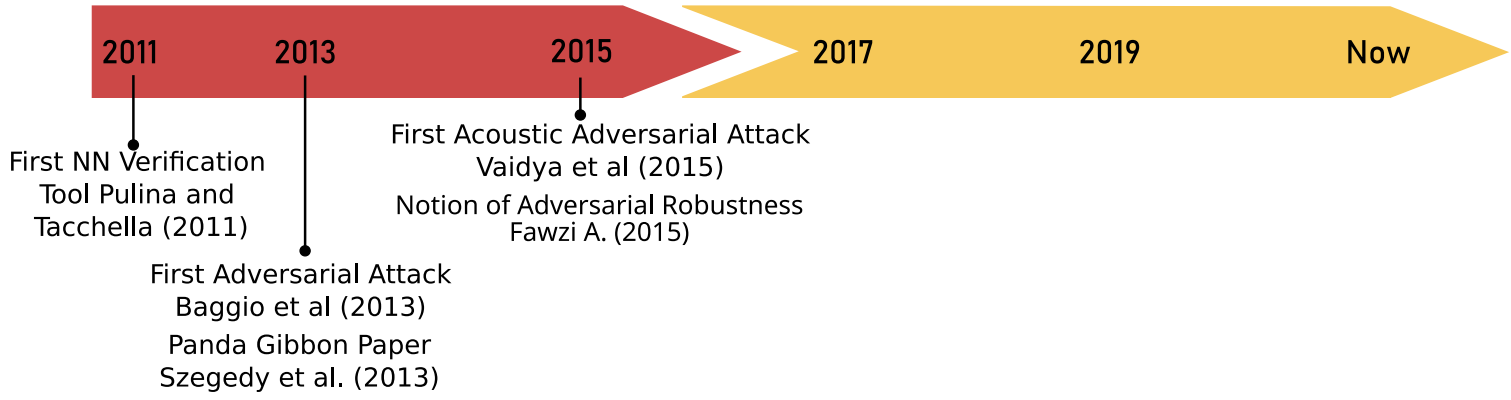
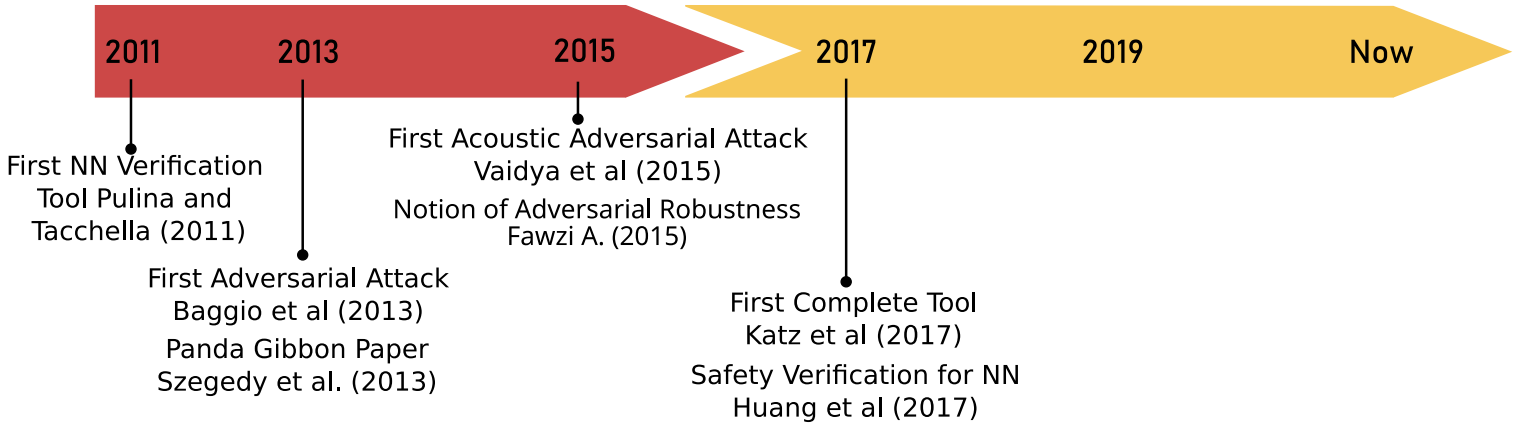
Casadio, M., Komendantskaya, E., Daggitt, M.L., Kokke, W., Katz, G., Amir, G., Refaeli, I.: Neural network robustness as a verification property: A principled case study. In: Computer Aided Verification (CAV 2022).

Overview of The Verification Landscape



What tools are available?
2015

Overview of The Verification Landscape



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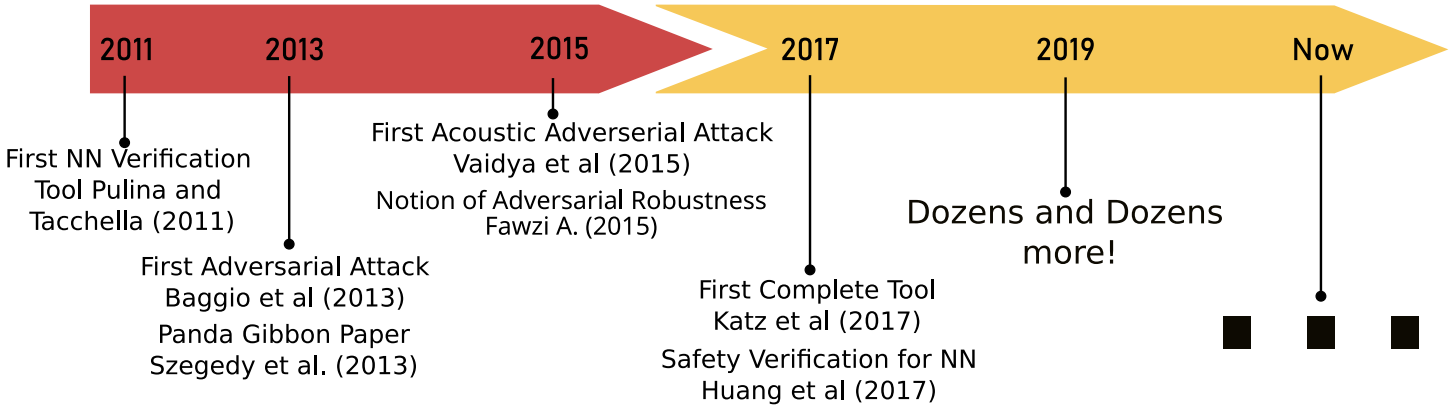

Current Verifier Landscape

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- ...

International Standards and Competitions

https://www.vnnlib.org/

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Marabou is our 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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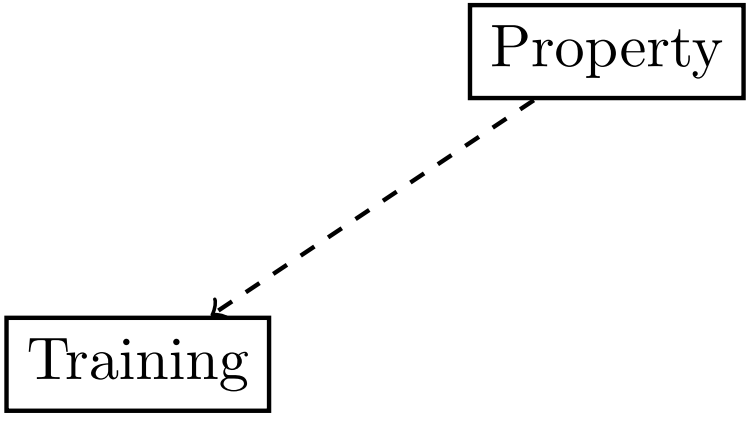

DL2
ACT
etc.

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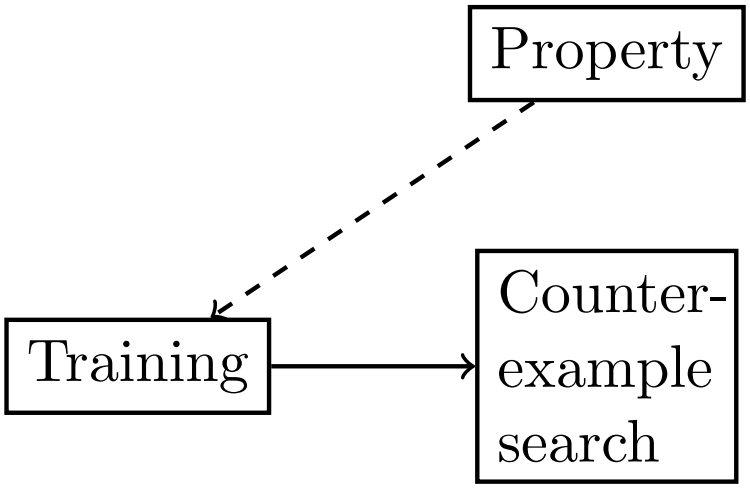

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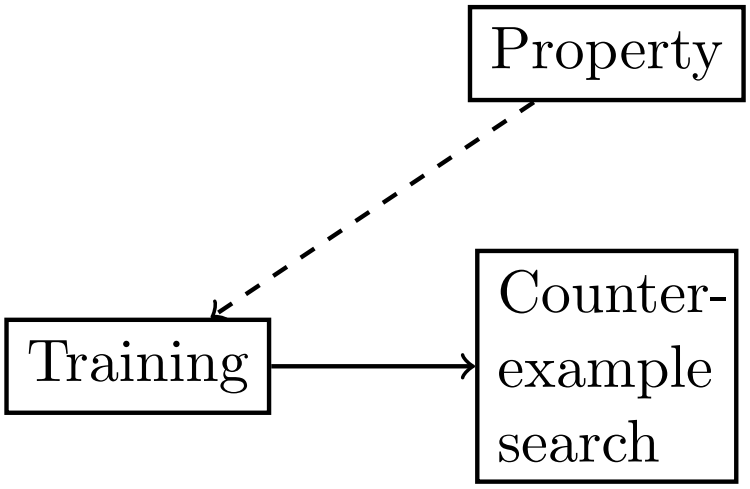

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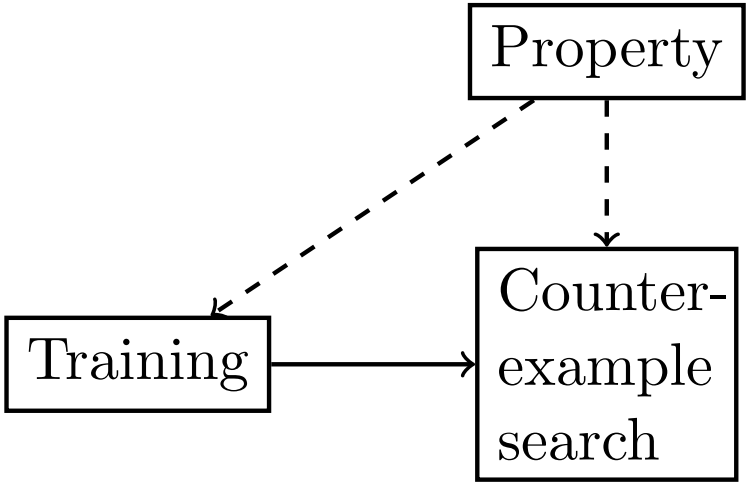

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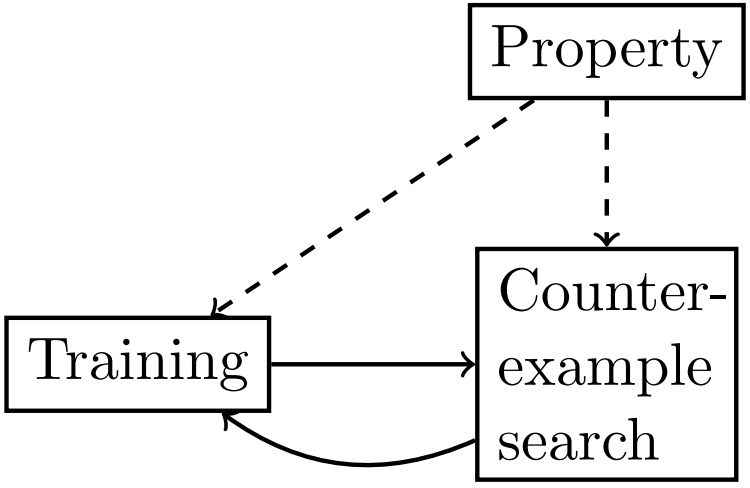

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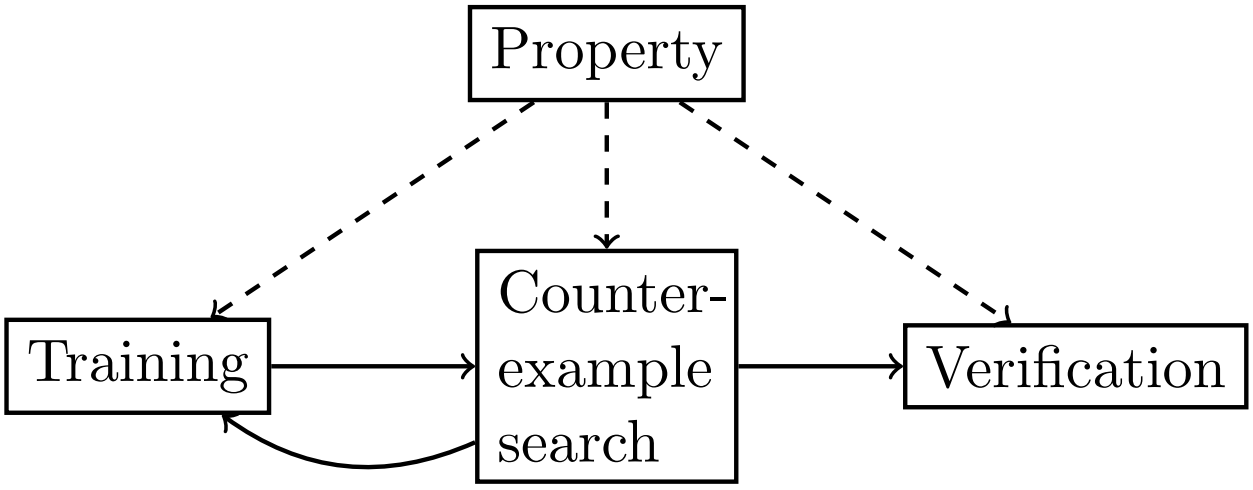

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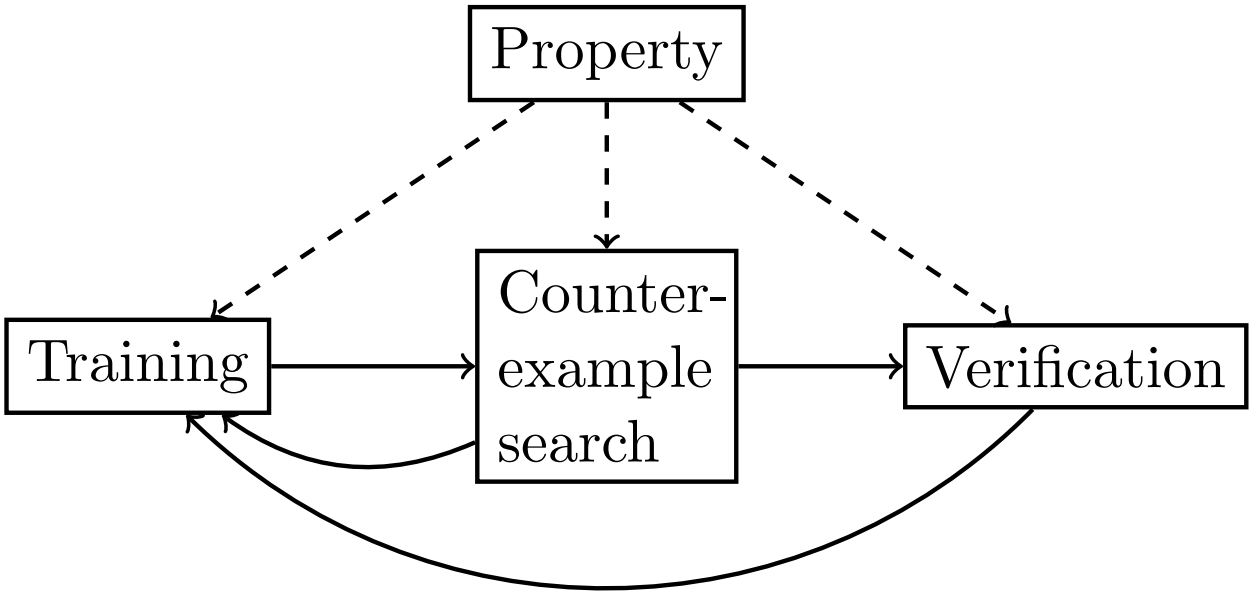

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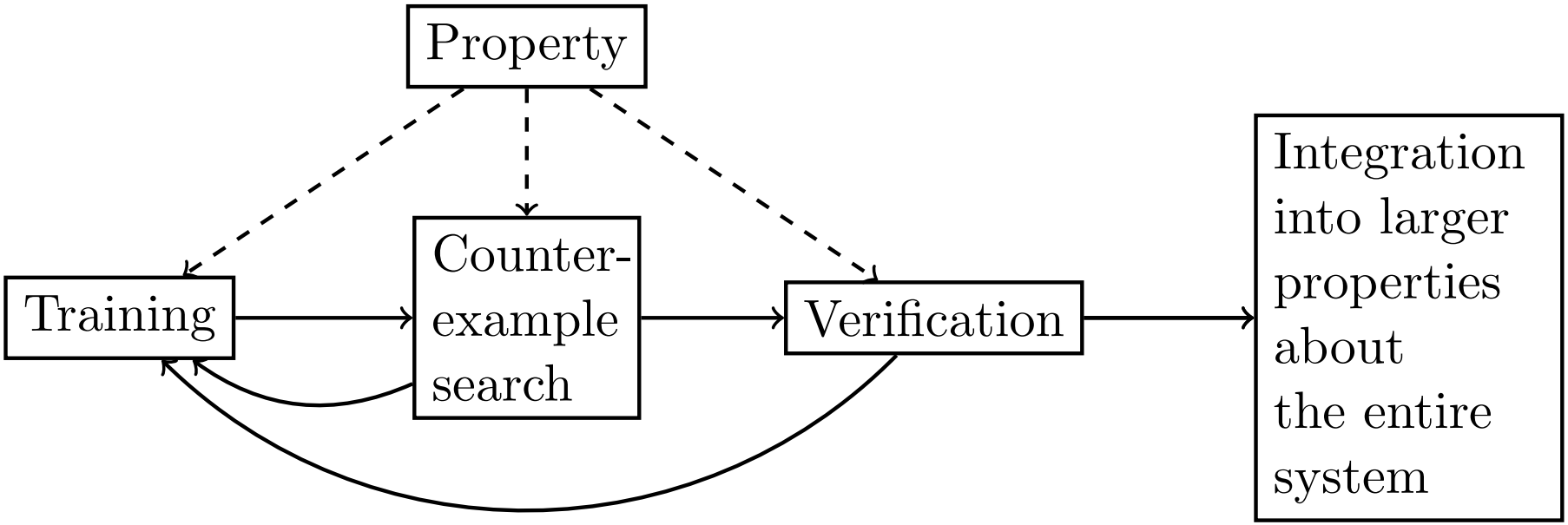

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- ML: understanding and integrating property-driven training
- Programming: finding the right languages to support these developments
- Complex systems: integration of neural net verification into complex systems

How BIG is the problem?

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

```
[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?

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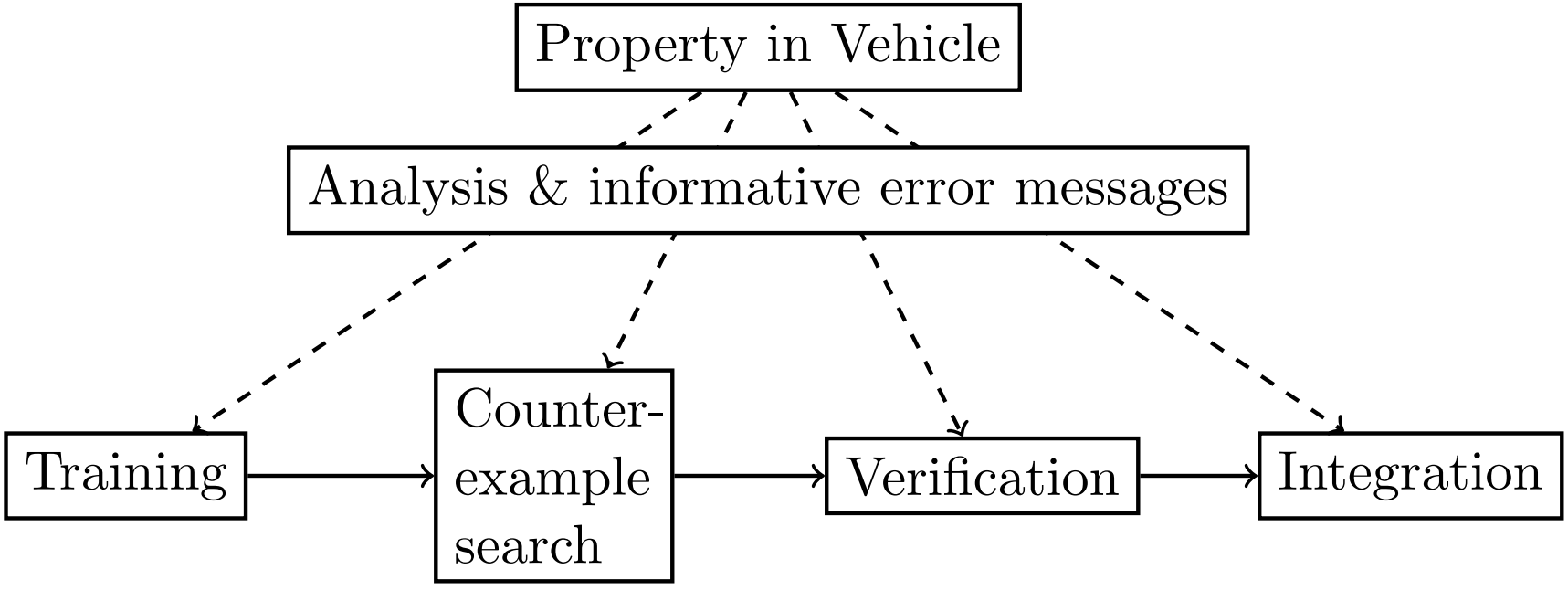
Recap: What are the problems?

- Interoperability - properties are not portable between training/counter-example search/ verification.
- Interpretability - code is not easy to understand.
- Integration - properties of networks cannot be linked to larger control system properties.

Vehicle ...

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



DL2	PGD	Marabou	Agda
ACT	FGSM	Eran	Imandra
etc.	etc.	etc.	KeymaeraX
			etc.

Table of Contents

Neural Network Verification: overview of the new domain

The lifecycle of neural network verification

Introduction to Vehicle (a mini tutorial)

Types

Let us build the ACAS Xu specification.
We start with types of input and output vectors, as well as types of ACAS Xu networks

```
type InputVector = Vector Rat 5
type OutputVector = Vector Rat 5

@network
acasXu : InputVector -> OutputVector
```

The Vector type represents a mathematical vector, or in programming terms can be thought of as a fixed-length array.

Values

Types for values are automatically inferred by **Vehicle**. For example, we can declare the number π and its type will be inferred as rational:

```
pi = 3.141592
```

Working with Vectors

- some input or output pre-processing maybe expected when defining a neural network.

Example

It is assumed that the ACAS Xu inputs and outputs are normalised, i.e. the network does not work directly with units like m/s. However, the specifications we want to write should ideally concern the original units.

Working with Vectors

- some input or output pre-processing maybe expected when defining a neural network.

Example

It is assumed that the ACAS Xu inputs and outputs are normalised, i.e. the network does not work directly with units like m/s. However, the specifications we want to write should ideally concern the original units.

- This is an instance of "problem space / input space mismatch"
- ... that is very common in neural net verification
- Being able to reason about problem space (alongside the input space) is a feature that distinguishes **Vehicle** from majority of the mainstream neural network verifiers

Vector Normalisation

For clarity, we define a new type synonym for unnormalised input vectors which are in the problem space.

```
type UnnormalisedInputVector = Vector Rat 5
```

Next we define the range of the inputs that the network is designed to work over.

```
minimumInputValues : UnnormalisedInputVector
minimumInputValues = [0,0,0,0,0]

maximumInputValues : UnnormalisedInputVector
maximumInputValues = [60261.0, 2*pi, 2*pi, 1100.0, 1200.0]

meanScalingValues : UnnormalisedInputVector
meanScalingValues = [19791.091, 0.0, 0.0, 650.0, 600.0]
```

Vector manipulation

An alternative method to vector definition is to use the ‘foreach‘ constructor, which is used to provide a value for each ‘index i‘.

```
minimumInputValues : UnnormalisedInputVector
minimumInputValues = foreach i . 0
```

Let us see how ‘foreach‘ works with vector indexing.
We can now define the normalisation function that takes an input vector and returns the unnormalised version.

```
normalise : UnnormalisedInputVector -> InputVector
normalise x = foreach i .
  (x ! i - meanScalingValues ! i) / (maximumInputValues ! i)
```

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... our first acquaintance with functions!

Functions and Types

```
<name> : <type>
<name> [<args>] = <expr>
```

Functions make up the backbone of the **Vehicle** language.

Functions and Types

```
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Functions make up the backbone of the **Vehicle** language.

```
validInput : UnnormalisedInputVector -> Bool
validInput x = forall i .
  minimumInputValues ! i <= x ! i <= maximumInputValues ! i
```

Functions and Types

```
<name> : <type>
<name> [<args>] = <expr>
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Functions make up the backbone of the **Vehicle** language.

```
validInput : UnnormalisedInputVector -> Bool
validInput x = forall i .
  minimumInputValues ! i <= x ! i <= maximumInputValues ! i
```

Our first acquaintance with quantifiers!

One of the main advantages of **Vehicle** is that it can be used to state and prove specifications that describe the network's behaviour over an infinite set of values.

Functions and Types

Function Composition: Exercise!

```
normAcasXu : UnnormalisedInputVector -> OutputVector
normAcasXu x = acasXu (normalise x)
```

Pre-defined functions and predicates

We have already used:

```
*
/
!
<=
```

Exercise

What do they stand for?

Lets verify ACAS Xu!

```
distanceToIntruder = 0    -- measured in metres
angleToIntruder    = 1    -- measured in radians
intruderHeading    = 2    -- measured in radians
speed              = 3    -- measured in metres/second
intruderSpeed      = 4    -- measured in meters/second

clearOfConflict = 0
weakLeft        = 1
weakRight       = 2
strongLeft      = 3
strongRight     = 4
```

The fact that all vector types come annotated with their size means that it is impossible to mess up indexing into vectors, e.g. if you changed ‘distanceToIntruder = 0‘ to ‘distanceToIntruder = 5‘ the specification would fail to type-check.

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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```
intruderDistantAndSlower : UnnormalisedInputVector -> Bool
intruderDistantAndSlower x =
  x ! distanceToIntruder >= 55947.691 and
  x ! speed              >= 1145      and
  x ! intruderSpeed      <= 60
```

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Exercise!

1. Can you identify whether the specification is written in terms of input space or problem space? How do you know?
2. Can you spot more pre-defined **Vehicle** functions? What are they?

There is little left to do!

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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.

```
@property
property1 : Bool
property1 = forall x .
   validInput x and intruderDistantAndSlower x =>
           normAcasXu x ! clearOfConflict <= 1500
```

There is little left to do!

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.

```
@property
property1 : Bool
property1 = forall x .
   validInput x and intruderDistantAndSlower x =>
           normAcasXu x ! clearOfConflict <= 1500
```

Exercise!

1. Can you guess the purpose of the syntax

   ```
   @property
   ```

   ?

2. What kind of domain ‘forall‘ ranges over? Is it finite or infinite?

How to run Vehicle

Checklist

1. a verifier installed (Marabou);
2. the actual network is supplied in an ONNX format
3. **Vehicle** is installed.

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1. a verifier installed (Marabou);
2. the actual network is supplied in an ONNX format
3. **Vehicle** is installed.

```
vehicle --compileAndVerify
  --specification acasXu.vcl
  --verifier Marabou
  --network acasXu:acasXu_1_7.onnx
  --property property1

-------------------------------------------------
Verifying properties:
  property1 [============================] 1/1 queries complete
Result: true
   property1
```

Exercise: ϵ-ball Robustness

```
type Image = Tensor Rat [28, 28]
type Label = Index 10
validImage : Image -> Bool
validImage x = forall i j . 0 <= x ! i ! j <= 1

@network
classifier : Image -> Vector Rat 10

advises : Image -> Label -> Bool
advises x i = forall j . j != i => classifier x ! i > classifier x ! j

@parameter
epsilon : Rat

boundedByEpsilon : Image -> Bool
boundedByEpsilon x = forall i j . -epsilon <= x ! i ! j <= epsilon

robustAround : Image -> Label -> Bool
robustAround image label = forall pertubation .
  let perturbedImage = image - pertubation in
  boundedByEpsilon pertubation and validImage perturbedImage =>
    advises perturbedImage label

@dataset
trainingImages : Vector Image n

@dataset
trainingLabels : Vector Label n

@property
robust : Vector Bool n
robust = foreach i . robustAround (trainingImages ! i) (trainingLabels ! i)
```

Vehicle ...

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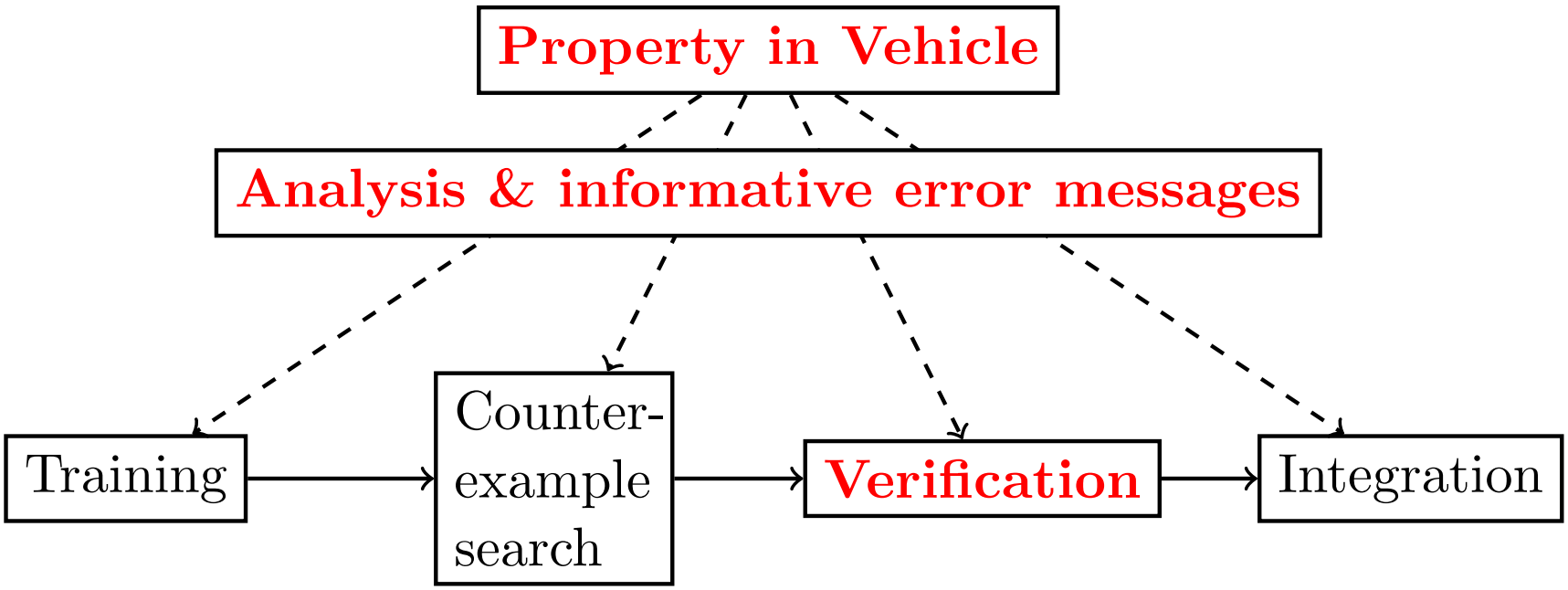

DL2	PGD	**Marabou**	Agda
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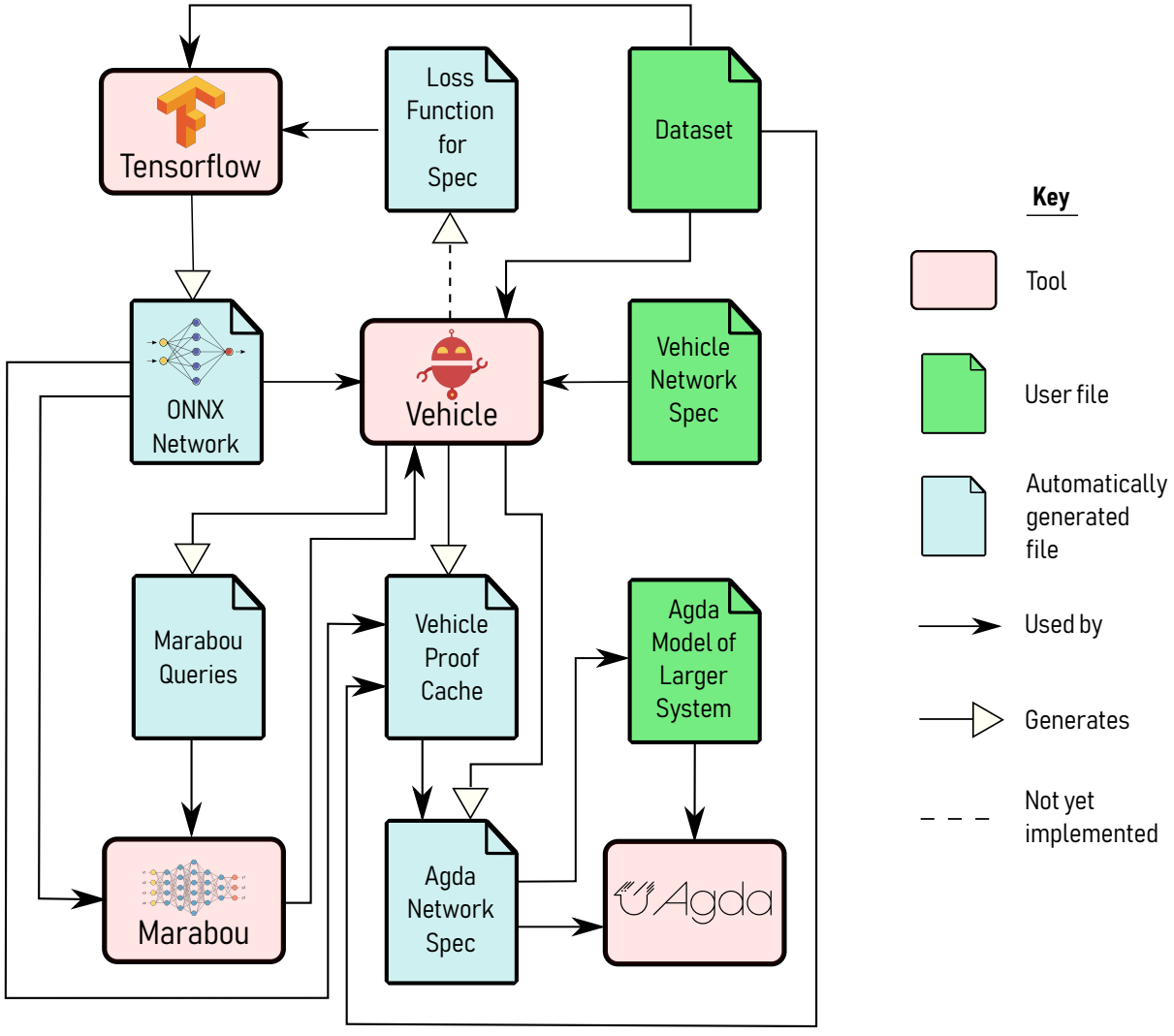
			etc.

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

Vehicle Team: The Vehicle language: `https://github.com/vehicle-lang` 2023.

M.Daggitt and W.Kokke: Vehicle User Manual. 2023.

Which 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