



Vehicle Tutorial Chapter 1: Getting Started

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

In this chapter...



We will:

- ▶ ... introduce main building blocks of **Vehicle** as a programming language

In this chapter...



We will:

- ▶ ... introduce main building blocks of **Vehicle** as a programming language
- ▶ ... get to practice working with **Vehicle**

In this chapter...



We will:

- ▶ ... introduce main building blocks of **Vehicle** as a programming language
- ▶ ... get to practice working with **Vehicle**
- ▶ ... use the famous ACAS Xu benchmark to show **Vehicle**'s work flow – from specification to verification

In this chapter...



We will:

- ▶ ... introduce main building blocks of **Vehicle** as a programming language
- ▶ ... get to practice working with **Vehicle**
- ▶ ... use the famous ACAS Xu benchmark to show **Vehicle**'s work flow – from specification to verification
- ▶ ... identify PL problems that are resolved by **Vehicle**

Recap: four PL problems



Recap: four PL problems



- I^O Interoperability – properties are not portable between training/counter-example search/ verification.
- I^P Interpretability – code is not easy to understand.
- I^J 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).

Recap: ACAS Xu



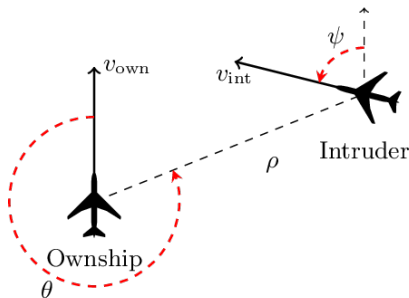
A collision avoidance system for unmanned autonomous aircraft.

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





Definition (ACAS Xu: Property 3)

If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

$$\begin{aligned} &1500 \leq \rho \leq 1800 \wedge \\ &-0.06 \leq \theta \leq 0.06 \wedge \\ &\psi \geq 3.10 \wedge \\ &v_{own} \geq 980 \wedge \\ &v_{int} \geq 960 \Rightarrow \\ &\text{the score for COC} \neq 0 \end{aligned}$$

Table of Contents



Vehicle' Syntax



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.



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)
```


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)  
... 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



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

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>
```

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 predicates and 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.



Function Composition: Exercise

What are the types of functions ‘acasXu’ and ‘normalise’:

```
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 3



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

Property 3



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

```
directlyAhead : UnnormalisedInputVector -> Bool
directlyAhead x =
  1500 <= x ! distanceToIntruder <= 1800 and
  -0.06 <= x ! angleToIntruder <= 0.06
```

Property 3



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

```
directlyAhead : UnnormalisedInputVector -> Bool
directlyAhead x =
  1500 <= x ! distanceToIntruder <= 1800 and
  -0.06 <= x ! angleToIntruder    <= 0.06
```

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 another pre-defined **Vehicle** function? What is it?

Property 3



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

Property 3



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

```
movingTowards : UnnormalisedInputVector -> Bool
```

```
movingTowards x =
```

```
  x ! intruderHeading >= 3.10  and
```

```
  x ! speed           >= 980   and
```

```
  x ! intruderSpeed   >= 960
```

Property 3



If the intruder is directly ahead and is moving towards the ownship, the score for **COC** will not be minimal.

```
movingTowards : UnnormalisedInputVector -> Bool
movingTowards x =
  x ! intruderHeading >= 3.10  and
  x ! speed            >= 980   and
  x ! intruderSpeed    >= 960
```

Exercise!

1. Can you spot one more pre-defined **Vehicle** function? What is it?

There is little left to do!



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

There is little left to do!



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

```
@property
property3 : Bool
property3 = forall x . validInput x and
                      directlyAhead x and
                      movingTowards x =>
    not (advises clearOfConflict x)
```

There is little left to do!



If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.

```
@property
property3 : Bool
property3 = forall x . validInput x and
                        directlyAhead x and
                        movingTowards x =>
    not (advises clearOfConflict x)
```

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.

How to run Vehicle



Checklist

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

```
vehicle verify \  
  --specification acasXu.vcl \  
  --verifier Marabou \  
  --network acasXu:acasXu_1_7.onnx \  
  --property property3
```

Verifying properties:

```
property3 [=====] 1/1 queries  
result: counterexample found  
x: [1799.9886669999978, 1.9509286320000003e-2,  
    3.09999732192, 980.0, 1017.6036]
```

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 perturbation .
  let perturbedImage = image - perturbation in
    boundedByEpsilon perturbation and validImage perturbedImage =>
      advises perturbedImage label

@dataset
trainingImages : Vector Image n

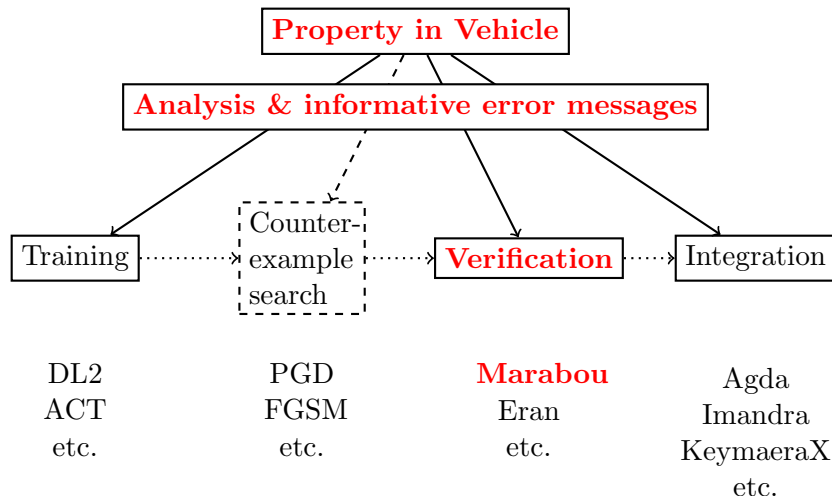
@dataset
trainingLabels : Vector Label n

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

Vehicle ...



the part that we have seen



Concluding Exercise



Which of the four PL problems we addressed?

- 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).

Exercise: ACAS Xu Property 1

ACAS Xu Property 1 gives an idea how the *embedding gap* can arise not only when we reason about inputs, but also the outputs of networks!



- ▶ Can you formalise Property 1 in Vehicle?
- ▶ Can you spot the instance of the embedding gap, this time concerning the network's output?

Exercise: ACAS Xu Property 1



ACAS Xu Property 1 gives an idea how the *embedding gap* can arise not only when we reason about inputs, but also the outputs of networks!

- ▶ Can you formalise Property 1 in Vehicle?
- ▶ Can you spot the instance of the embedding gap, this time concerning the network's output?

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:

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

Exercise: ACAS Xu Property 1



ACAS Xu Property 1 gives an idea how the *embedding gap* can arise not only when we reason about inputs, but also the outputs of networks!

- ▶ Can you formalise Property 1 in Vehicle?
- ▶ Can you spot the instance of the embedding gap, this time concerning the network's output?

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:

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

Note:

The ACAS Xu neural network outputs are scaled as follows: given an element x of the output vector, we scale it as: $\frac{x-7.518884}{373.94992}$.

Plan for the rest of this tutorial



- ▶ Before coffee break:
 - ▶ **Exercise session:** write and verify your own specs (with possibility to extend over the break)
 - ▶ for writing a spec, install vehicle: just run
`pip install vehicle-lang`
 - ▶ for verifying a spec, you also need Marabou installed
`pip install maraboupy`

Exercises



Robustness (for those familiar with the problem)

- ▶ Fill in missing code in the Robustness spec available at <https://github.com/vehicle-lang/tutorial:exercises/Chapter2.GettingStarted/mnist-robustness>
- ▶ Using networks and data given in same folder, verify robustness via Vehicle.

Robustness (for those NOT familiar with the problem)

Study the chapter "Proving Neural Network Robustness" here:
<https://vehicle-lang.github.io/tutorial/>

More ACAS Xu properties in the same spec

- ▶ Extend the given ACAS Xu specification with Property 1. The spec and network can be found at:
<https://github.com/vehicle-lang/tutorial, at examples/Chapter2.GettingStarted/acasXu>
- ▶ Using the networks and data given in same folder, verify the properties via Vehicle.