Vehicle Tutorial Chapter 1: Getting Started

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In this chapter...

We will:

- ... introduce Main building blocks of Vehicle as a Programming Language

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- ... 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 (cf Introduction) that are resolved by Vehicle

Recap: four PL problems

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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).

Recap: ACAS Xu

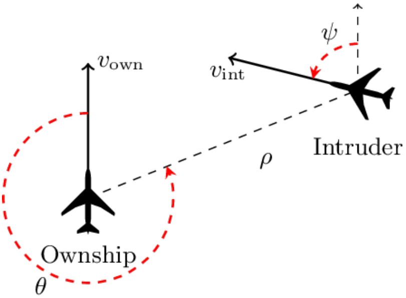
A collision avoidance system for unmanned autonomous aircraft.

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



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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.

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

Table of Contents

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.

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

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.

Functions and types

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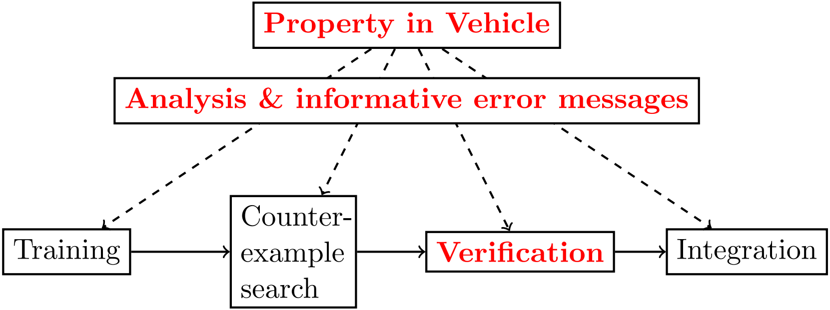
```
vehicle --compileAndVerify
  --specification acasXu.vcl
  --verifier Marabou
  --network acasXu:acasXu_1_7.onnx
  --property property1

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

Next Chapter 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 ...

the part that we have seen



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

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.
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