An aerial photograph of the Seattle skyline, featuring the Space Needle prominently in the foreground. The city's dense urban landscape is visible, with various high-rise buildings and green spaces. The sky is a clear blue with some light, wispy clouds. The text of the presentation is overlaid on a dark, semi-transparent rectangular area in the center of the image.

Neural Network Verification With Vehicle:

Chapter 3 - Robustness

ICFP'23 Tutorial

Matthew Daggitt ¹ Wen Kokke (online) ² Ekaterina Komendantskaya ³

¹Heriot-Watt University · ²University of Strathclyde · ³University of Southampton



Again - The elephant ... panda... gibbon? in the room



“panda”

57.7% confidence

+ .007 ×



noise

=



“gibbon”

99.3% confidence

Goodfellow, I. J., Shlens, J., & Szegedy, C. (2014). *Explaining and harnessing adversarial examples*. *arXiv preprint arXiv:1412.6572*.



This is what a simple Neural Network Property Looks like

Simple NN Property

Let f be the neural network

Let \hat{x} be an input in the training set

Let $|\cdot - \cdot|$ be some notion of distance

Then

$$\forall x : |x - \hat{x}| \leq \epsilon \implies |f(x) - f(\hat{x})| \leq \delta$$



In Practice - Robustness of MNIST

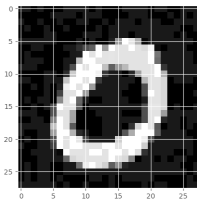
Let us take as an example the famous MNIST data set by LeCun et al. The images look like this:



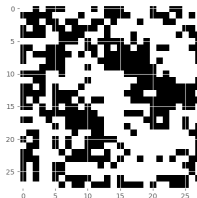


In Practice - Robustness of MNIST

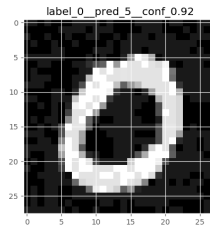
Predicted "0" 99%



Small perturbation



Predicted "5" 94%





Formal Verification of NN (more details)

Definition of Verification for a Black Box Model

For a neural network $N : \hat{x} \rightarrow \hat{y}$, the input property $P(\hat{x})$ and the output property $Q(\hat{y})$, does there exist an input \hat{x}_0 which satisfies $P(\hat{x}_0)$ such that its corresponding output \hat{y}_0 satisfies $Q(\hat{y}_0)$?

- ▶ $P(\hat{x})$ characterises inputs checked
- ▶ $Q(\hat{y})$ characterises the behaviour we **DO NOT** wish for
- ▶ if satisfied, counterexample is returned, else property holds
- ▶ the P for robustness is $|\hat{x} - \hat{x}_0|_{L_\infty} \leq \epsilon$ (more on this later)
- ▶ the Q is, $\bigvee_i (\hat{y}[i_0] \leq \hat{y}[i])$, where $\bar{y}[i_0]$ is the desired label



Or More Simply: Robustness

ϵ -ball robustness**

Formally, we define an ϵ -ball around an image $\hat{\mathbf{x}}$ as:

$$\mathbb{B}(\hat{\mathbf{x}}, \epsilon) = \{\mathbf{x} \in \mathbb{R}^n : |\hat{\mathbf{x}} - \mathbf{x}| \leq \epsilon\}$$

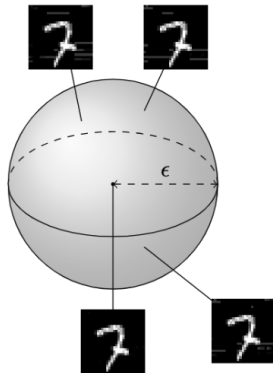
where $|\dots|$ is a distance function (or L -norm) in \mathbb{R}^n , such as Euclidean distance or L_∞ -norm.

**There are various types of these



ϵ -ball Visualised

For every image in the dataset, we assume we can “draw” a small ϵ -ball around it, and guarantee that within that ϵ -ball classification of the network does not change much





How to Specify this in Vehicle?



Formalising ϵ -ball robustness for MNIST networks in Vehicle

- ▶ We will see how Vehicle can be used to handle properties that refer directly to the data sets.
- ▶ How to specify images (represented as 2D arrays)
- ▶ User defined parameters in Vehicle
- ▶ Verification of properties



Vehicle Language Overview

Language Overview

The Vehicle language contains the following basic types:

- ▶ **Bool** - booleans
 - ▶ Operations: `and`, `or`, `=>`, `not`, `if ... then ... else ...`, `==`, `!=`
- ▶ **Index** `n` - natural numbers between 0 (inclusive) and `n` (exclusive).
 - ▶ Used for safe indexing into tensors. For example, only the values 0 and 1 have type **Index** 2.
 - ▶ Operations: `==`, `!=`, `<=`, `>=`, `<`, `>`
- ▶ **Nat** - natural numbers
 - ▶ Operations: `==`, `!=`, `<=`, `>=`, `<`, `>`, `+`, `*`
- ▶ **Int** - integer numbers
 - ▶ Operations: `==`, `!=`, `<=`, `>=`, `<`, `>`, `+`, `*`, `-`
- ▶ **Rat** - rational numbers
 - ▶ Operations: `==`, `!=`, `<=`, `>=`, `<`, `>`, `+`, `*`, `-`, `/`



Vehicle Language Overview

Language Overview (continued)

Next there are two container types:

- ▶ **List A** - a list of elements of type **A**
 - ▶ Used for sequences of data for which one either doesn't care about or don't know the length of.
 - ▶ Operations: `==`, `!=`, `map`, `fold`
- ▶ **Tensor A** [d_1 , ..., d_n] - a tensor of elements of type **A** with dimensions $d_1 \times \dots \times d_n$.
 - ▶ Used for data for which it is important to know the size of. Due to the dependently typed-nature of the language, the dimensions can themselves be arbitrary expressions.
 - ▶ Operations: `==`, `!=`, `map`, `fold`, `!`



Vehicle Language Overview

Special Mentions: Functions, Networks and Datasets

- ▶ The function type is written $A \rightarrow B$ where A is the input type and B is the output type e.g.

```
add2 : Nat -> Nat
```

```
add2 x = x + 2
```

- ▶ The language models neural networks as black box functions between tensors

```
@network
```

```
network myNetwork : Tensor Rat [28, 28] -> Tensor Rat [10]
```

- ▶ Datasets may be introduced using the `dataset` keyword:

```
@dataset
```

```
dataset myDataset : Tensor Rat [10, 784]
```



Vehicle Language Overview

Special Mentions: Parameters, Quantifiers and Type Synonyms

- Sometimes the user may not want to hard-code a specific value but rather provide a compile time variable:

```
@parameter
```

```
parameter myParameter : Rat
```

- universal (`forall`) and existential (`exists`) quantifiers e.g.

```
condition : Bool
```

```
condition = forall x . lastOutputPositive x
```

- can declare synonym for types e.g.:

```
type Image = Tensor Rat [28, 28]
```

```
@network
```

```
network classify : Image -> Tensor Rat [10]
```



Case Study: Initialisation - 2D Arrays and Labels

Declare input as 2d array (with a label)

```
type Image = Tensor Rat [28, 28]
```

```
type Label = Index 10
```

```
type LabelDistribution = Tensor Rat [10]
```

Define what a valid input is (images are within 0 and 1)

```
valid : Image -> Bool
```

```
valid x = forall i j . 0 <= x ! i ! j <= 1
```



Let's give it a go!



Case Study: Classifier - Network and Prediction

The output of the network is a score for each of the digits 0 to 9.

```
@network
classifier : Image -> LabelDistribution
```

The classifier advises that input image x has label i if the score for label i is greater than the score of any other label j :

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



Case Study: Robustness - User Parameters and Bounds

define the parameter** epsilon that will represent the radius of the balls that we verify.

```
@parameter
```

```
epsilon : Rat
```

we define what it means for an image x to be in a ball of size epsilon

```
boundedByEpsilon : Image -> Bool
```

```
boundedByEpsilon x = forall i j .
```

```
  -epsilon <= x ! i ! j <= epsilon
```

**N.B @parameter will mean it is specified at runtime



Case Study: Robustness - Robust Around a Point

We now define what it means for the network to be robust around an image x that should be classified as y

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



Case Study: Robustness - Robust Image Classification

Size of input automatically inferred by tool at runtime

```
@parameter(infer=True)
n : Nat
```

We next declare two dataset (parameter ensures same size)

```
@dataset
trainingImages : Vector Image n
@dataset
trainingLabels : Vector Label n
```



Case Study: Robustness - Robust Image Classification (continued)

We then say that the network is robust for this data set if it is robust around every pair of input images and output labels.

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



Full spec ϵ -ball Robustness

```

type Image = Tensor Rat [28, 28]
type Label = Index 10
@network
classifier : Image -> Vector Rat 10
@parameter
epsilon : Rat

validImage : Image -> Bool
validImage x = forall i j . 0 <= x ! i ! j <= 1

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

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)

```



Case Study: Robustness - Verification

In order to run Vehicle, we need to provide:

- ▶ the specification file,
- ▶ the network in ONNX format,
- ▶ the data in idx format,
- ▶ and the dedired ϵ value.



Case Study: Robustness - Verification (continued)

Putting it all together

```
vehicle verify \  
  --specification mnist-robustness.vcl \  
  --network classifier:mnist-classifier.onnx \  
  --parameter epsilon:0.005 \  
  --dataset trainingImages:images.idx \  
  --dataset trainingLabels:labels.idx \  
  --verifier Marabou
```




Concluding Exercise

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 and input space.

Question. Which of these have we addressed in this chapter?



Conclusions

What to setup for next session + Exercises!

- ▶ Robustness is currently the most verified property in AI
- ▶ You should now be familiar with how to specify this and verify networks in Vehicle
- ▶ Coming Next after the break:
 1. **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`
 2. Property driven training in Vehicle
 3. Integration with Interactive Theorem Provers (Agda)
 4. Practical applications of AI verification



Exercises

Easy

Robustness (for those familiar with the problem)

- ▶ Run and try a variety of ϵ -values The spec and network can be found at:
<https://github.com/vehicle-lang/tutorial:exercises/Chapter2.GettingStarted/mnist-robustness>
- ▶ Using the given networks and data, verify robustness via Vehicle.
- ▶ Exercises 3.5.1, 3.5.2 and 3.5.3

Robustness (for those NOT familiar with the problem)

Study the chapter “Proving Neural Network Robustness” here:

<https://vehicle-lang.github.io/tutorial/>



Exercises

More Advanced

More Robustness properties in the same spec

- ▶ Fill in missing code in the Robustness spec available at <https://github.com/vehicle-lang/tutorial>, at `examples/Chapter3.Robustness/`
- ▶ Exercises 3.5.4, 3.5.5 and 3.5.6

Question. Does the different ϵ size make a difference?



Excercises

Further Robustness definitions

Try specifying another robustness property (e.g. SCR)

$\forall \mathbf{x} \in \mathbb{B}(\hat{\mathbf{x}}, \epsilon). \text{ robust}(f(\mathbf{x}))$

Property	Definition of Robust
CR (Classification Robustness)	$\operatorname{argmax} f(\mathbf{x}) = c$
SCR (Strong Classification Robustness)	$f(\mathbf{x})_c \geq \eta$
SR (Standard Robustness)	$ f(\mathbf{x}) - f(\hat{\mathbf{x}}) \leq \delta$
LR (Lipschitz Robustness)	$ f(\mathbf{x}) - f(\hat{\mathbf{x}}) \leq L \mathbf{x} - \hat{\mathbf{x}} $

Casadio, Marco, Matthew L. Daggitt, Ekaterina Komendantskaya, Wen Kokke, Daniel Kienitz, and Rob Stewart. 2021. "Property-Driven Training: All You (n) Ever Wanted to Know About."



Exercises

Even More Advanced

Train your own network, different distances, more datasets!

- ▶ Try out all other Exercises in:
<https://vehicle-lang.github.io/tutorial/#exercises>
- ▶ Exercise 3.5.7

That's all for Chapter 3 folks!