









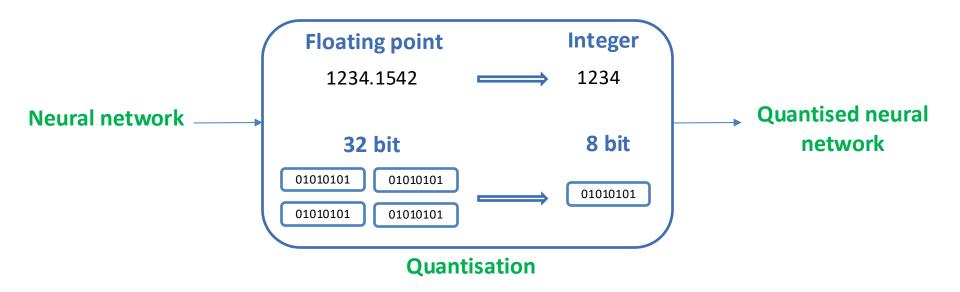
# Certifiably Quantisation-Robust Training and Inference of Neural Networks

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#### Overview

- 1. Introduction
- 2. Methods
- 3. Experiments
- 4. Discussion

#### Introduction



Formal guarantees on the behavior of quantised models?

#### Introduction

What are our contributions?

✓ Verification across *all possible quantised networks*, independent of specific schemes

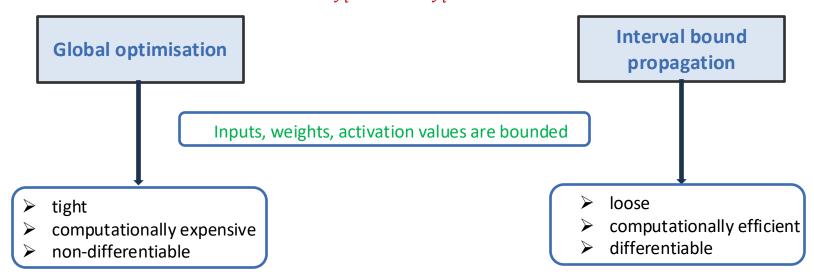
✓ Differentiable bounds that enable both verification and robust training.

✓ Formal guarantees for quantisation-robust neural networks.

#### Methods

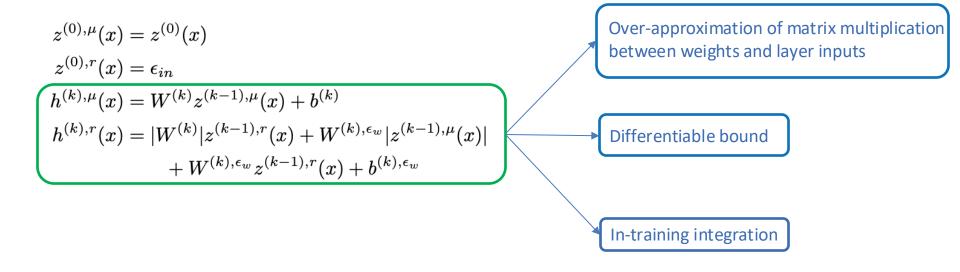
Verify all possible quantised networks, independent of specific

Find the worst-case scenario of each output dimension  $\hat{y}_i$  and  $\hat{y}_i$ 



#### Methods

#### **Differentiable bound Propagation for Quantisation-Robust Training**



#### **Experiments**

# Training a neural network with differentiable bound propagation technique improves its robustness

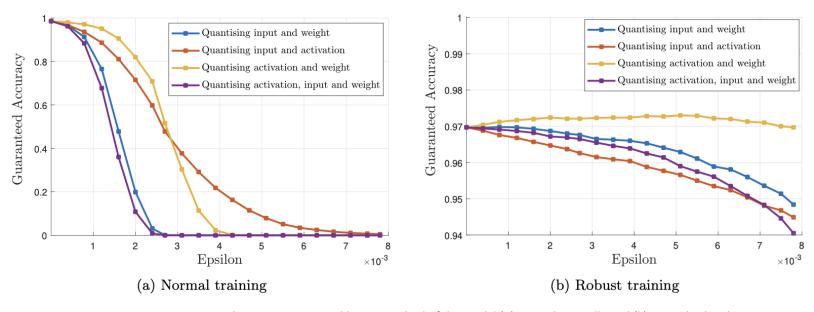


Figure 1: Guaranteed accuracy computed by IBP method of the model (a) trained normally and (b) trained robustly

## Experiments

Verification of all possible quantised networks parameterised by 6/8/10 bit quantisation diameters

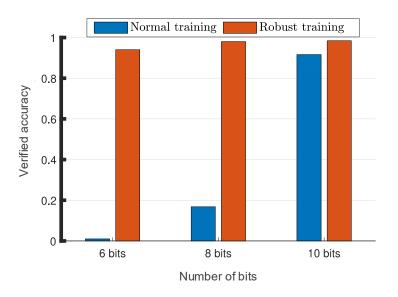


Figure 2: Comparison of normal training and robust training on verified accuracy computed by bilinear optimization method

## Experiments

#### Differentiable bound trained models are only robust but also easier to verify

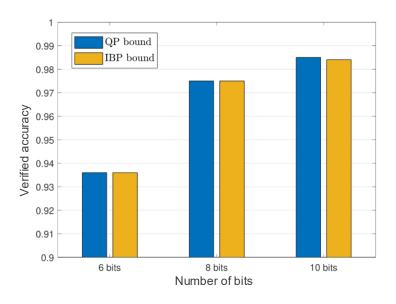


Figure 3: Verified accuracy computed by IBP and BP bounds on models trained via differentiable bound propagation technique

#### Discussion

 Proposing formal verification and training methods for the robustness of neural networks against quantisation of their inputs, parameters and activation values

The scalability of the verification and training methods