NeuroCodeBench: a plain C neural network benchmark for software verification

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EnnCore

MANCHESTER 1824
The University of Manchester

The abstraction ladder (1)

The "classic ML" mindset

- Define a neural net as $f : \mathbb{R}^n \to \mathbb{R}^m$
- Gradient descent, auto differentiation
- Data manifold, regularizers, ...

What's the implicit assumption?

- We live in a mathematician's world
- At a very high level of abstraction
- And operations have infinite precision

Very effective, most of the time

The abstraction ladder (2)

Quantisation efforts

- 16-bit floating point
- 16-bit, 8-bit, 4-bit integers
- Binarized neural networks

Parallel execution

- GPU, SIMD instructions, TPU, FPGAs
- Distributed/federated learning

What's the implicit assumption?

- We make a lot of optimisations
- But the result doesn't really change

The abstraction ladder (3)

The software safety mindset

- Buffer overflow, division by zero
- Data race, deadlock, use-after-free
- Infinite loops, side effects

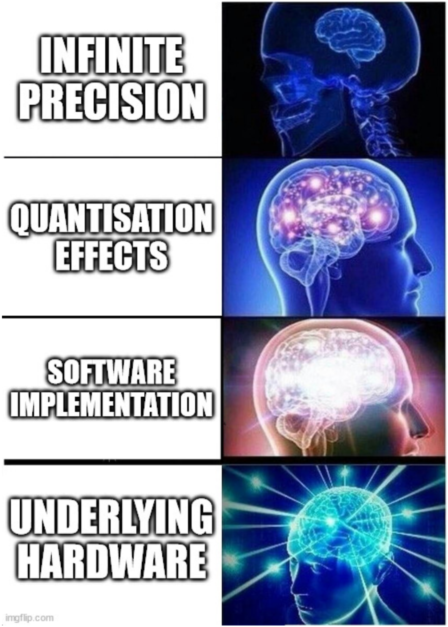
What's the implicit assumption

- Every innocent bug
- Can introduce a vulnerability

Just a problem for library makers?

The abstraction ladder (4)

Don't forget the hardware!


INFINITE PRECISION
QUANTISATION EFFECTS
SOFTWARE IMPLEMENTATION
UNDERLYING HARDWARE
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Implementation effects (1)

Can we expect consistent behaviour across devices?

- Cidon et al., *Characterizing and taming model instability across edge devices*, 2021
- Wang et al, *SysNoise: exploring and benchmarking trainin-deployment system inconsistency*, 2023

Many low-level sources of noise!

- Pre-processing: .jpg→tensor (iDCT, interpolation, colour)
- Model inference: convolutions, upsampling, floats, quantize
- Post-processing: tensor→bounding box (rounding coordinates)

Up to 6% accuracy fluctuation[1]

[1] Cidon [2021] runs MobileNetV2 on photos taken from five different phones.

Implementation effects (2)

Can we trust NN verifiers?

- VNN-COMP compares the best neural network verifiers
- Let's reproduce one of their results!

Benchmark: reach_prob_density/robot_11

- A ReLU network with architecture $5 \times 64 \times 64 \times 64 \times 5$
- Input assumption: $x_0 \in [-1.8, -1.2] \wedge x_1 \in [-1.8, -1.2]\ldots$
- Output assertion: $y_0 \geq 0.27 \wedge y_1 \in [-0.17, 0.17]\ldots$

Five tools return a counterexample!

- $\alpha\beta$-CROWN, Marabou, `nnenum`, VeriNet, Peregrinn

But none of them violates the output assertion[2]

[2] With the plain C code from `onnx2c` and the MinGW-w64 compiler.


YOU PROVED THAT A ML MODEL IS SAFE
YOUR GUARANTEE IS IMPLEMENTATION DEPENDENT
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Software verification

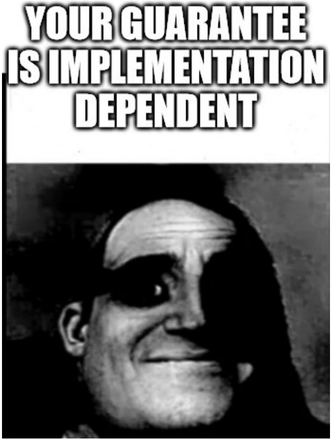
Advantages

- Code is a formal specification
- (just add safety properties)
- Decades of SV research
- Very sophisticated tools

Disadvantages

- Too many implementation details
- Memory model, parallelism
- Hard to scale to large instances

Is it a viable approach?



Develop
yet
another software
verifier

Check
the performance
of
existing ones

NeuroCodeBench (1)

Benchmarking goals

- Representativeness → realistic use cases
- Compatibility → SV likes plain C code
- Variety → from small to "large" instances
- Correctness → known ground truth

Our work is inspired by

- Microcontroller software

Short paper available!

- Manino et al., *NeuroCodeBench: a plain C neural network benchmark for software verification*, 2023
- `https://arxiv.org/abs/2309.03617`

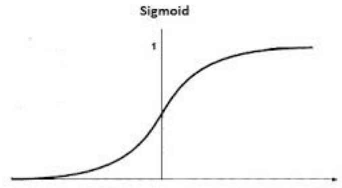
NeuroCodeBench (2)

Benchmark Category	Safe	Unsafe	Ground Truth
`math_functions`	33	11	A Priori
`activation_functions`	40	16	A Priori
`hopfield_nets`	47	33	A Priori
`poly_approx`	48	48	Brute Force
`reach_prob_density`	22	13	VNN-COMP'22
`reinforcement_learning`	103	193	VNN-COMP'22
Total	293	314	

Table: Overview of *NeuroCodeBench*. The "Unsafe" column comprises all properties for which a counterexample exists. The "Ground Truth" column reports the source of our verdicts.


Let's Play
Floating Point

Floating-point activations (1)



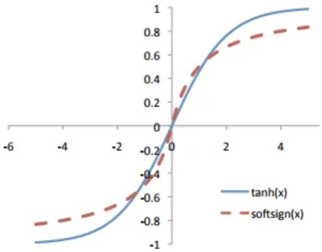
How to implement the sigmoid function?

- `s(float x){return 1.0f / (1.0f + expf(-x));}`
- `s(float x){return 0.5f * tanhf(0.5f * x) + 0.5f;}`

Let's compare them:

- Which one is faster?
- Which one is more precise?
- What happens for `x > 88.0f`?

Floating-point activations (2)



Implementing the softsign function:

- `s(float x){return x / (1.0f + fabsf(x));}`

Tricky questions:

- What happens for `x = -Inf`?
- Is our implementation always non-decreasing?


GAME OVER

NeuroCodeBench (3)

Functions from `math.h`

- expf, expm1f, logf, log1pf
- acosf, asinf, atanhf, cosf, sinf, tanhf
- erff, fabsf, fmaxf, sqrtf

Activation functions

- Elu, Gelu, Logistic, ReLU, Softmax, Softplus, Softsign, TanH

Safety properties (Examples)

- Output bounds: $expf(x) \geq 1 + x$
- Periodicity: $sinf(x) = sinf(x + 2\pi)$
- Symmetry: $tanhf(x) = -tanhf(-x)$
- Inversion: $expf(logpf(x)) = x$

Benchmark Category
`math_functions`
`activation_functions`
`hopfield_nets`
`poly_approx`
`reach_prob_density`
`reinforcement_learning`

```c
#include <verifier_functions.h>

#include <math.h>

float elu(float x)
{
        if(x >= 0.0f)
                return x;
        else
                return expm1f(x);
}
```

NeuroCodeBench (4)

Classic Hopfield Networks

- Recurrent architecture
- Hard-coded Hebbian weights
- Error-correcting behaviour

Our idea

- Reconstruct a single $x = (1, 1, \ldots, 1)$
- Use either softsign or tanh activations
- Vary code width and num of iterations

Safety properties

- Make $x_i \in [-1, +1]$ for $i <$ half width
- Can the network reach $x = (1, \ldots, 1)$?

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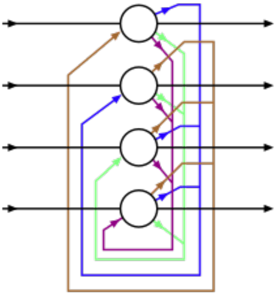

NeuroCodeBench (5)

Transfer function approximation

- Very common in engineering
- Approximate electrical equivalent

Our idea

- Fourth-order oscillating polynomial
- ReLUs, 1–4 layers, 16–1024 width

Safety properties

- Robustness of approximation
- $|\text{network}(x) - \text{poly}(x)| \leq \epsilon$
- for x around the worst-case

Benchmark Category
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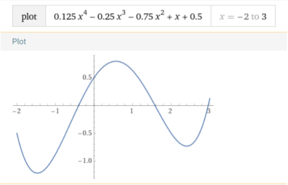

NeuroCodeBench (6)

Importing VNN-COMP benchmarks

- Choose categories from 2022 edition
- with very small neural networks

Converting to plain C code

- Turn ONNX into plain C with `onnx2c`
- Microcontroller-style minimalism

Safety properties

- Keep the original VNN-LIB properties
- Encode them as `assert`/`assume`
- Check validity of counterexamples

Benchmark Category
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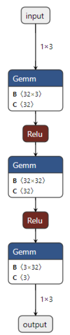

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COMPETITION
TIME!

Experimental results (1)

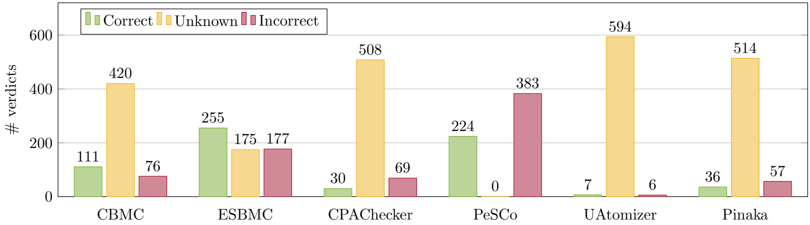
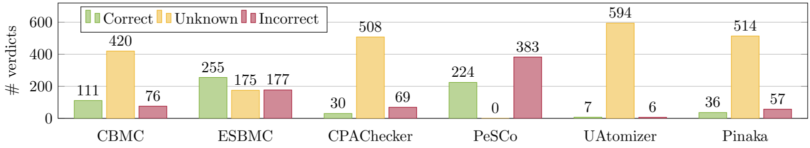


Figure: Results of state-of-the-art software verifiers after 900 seconds.

Experiments with off-the-shelf verifiers

- We pick the top scoring tools from SV-COMP 2022
- We keep the same settings of the reachability category
- Veriety of techniques: BMC, falsification, portfolios

Experimental results (2)



Reviewer 2 Must Be Stopped!

- ESBMC found 255 true properties, while PeSCo found 224.
- So, who is right? This odd behavior *must* be discussed.

Preliminary Analysis

- No support of mathematical libraries → incorrect results
- Cannot scale to large programs → unknown result (timeout)
- Other hidden bugs (floats, multi-dimensional arrays)?

Future work

Reproduce

- Submit *NeuroCodeBench* to SV-COMP 2023
- Experiments run by independent team
- Tool authors have a chance to fix bugs

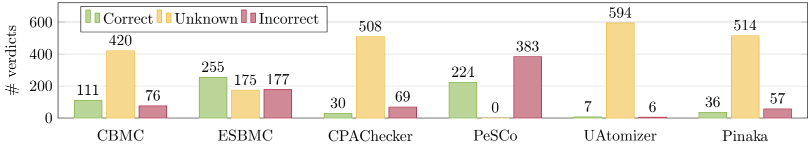
Improve

- More benchmarks, neural networks, use cases
- Operational models to support `math.h`

Generalise

- If verifying neural code is too challenging
- Can we reason about sets of implementations?

SV-COMP 2024



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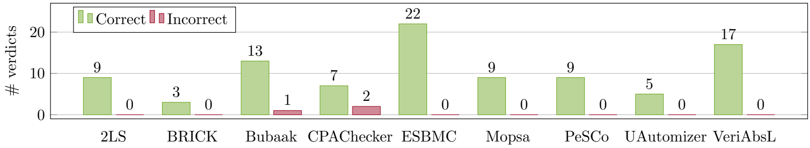

Figure: Results of various SV-COMP pre-runs (numbers may change).


You discover that verifiers are broken
THIS IS FINE.
But that means more future work!
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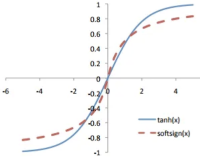
Floating-point activations (3)

```
float softsign(float x)
{ return x / (1.0f + fabsf(x)); }
```



Is our implementation always non-decreasing? No.[3]

- $x_1 = 15.000012397766113 \wedge x_2 = 15.000021934509277$
- $\mathit{softsign}(x_1) = 0.93750011920928955$
- $\mathit{softsign}(x_2) = 0.93750000000000000$
- $x_2 > x_1$ but $\mathit{softsign}(x_2) < \mathit{softsign}(x_1)$!
- It decreases by ≈ 0.00000012

[3] MinGW-w64 with options `-m64 -O2` and MUSL implementation of `math.h`.