



Machine Learning with Verifiable Guarantees

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Why Verify Neural Networks?

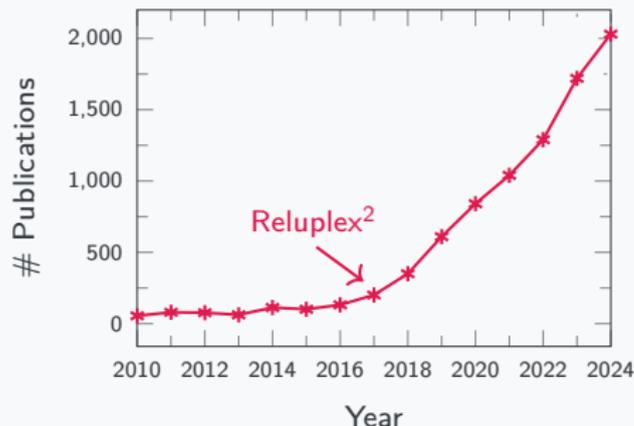


Figure: Stickers placed on a stop sign cause a neural network to misclassify it as *Speed Limit 45 mph*.¹

¹K. Eykholt et al. (2018). 'Robust Physical-World Attacks on Deep Learning Visual Classification'. In: *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. DOI: [10.1109/CVPR.2018.00175](https://doi.org/10.1109/CVPR.2018.00175).

How to Verify Neural Networks?

Paper titles containing “formal verification” and “neural network” over time



Community Efforts

VNN-COMP International Verification of Neural Networks

Competition (<https://sites.google.com/view/vnn2025>)

VNN-LIB International Standard for the Verification of Neural Networks (<https://www.vnnlib.org>)

²G. Katz et al. (2017). 'Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks'. In: *Computer Aided Verification*. DOI: [10.1007/978-3-319-63387-9_5](https://doi.org/10.1007/978-3-319-63387-9_5).

Training to Satisfy Constraints

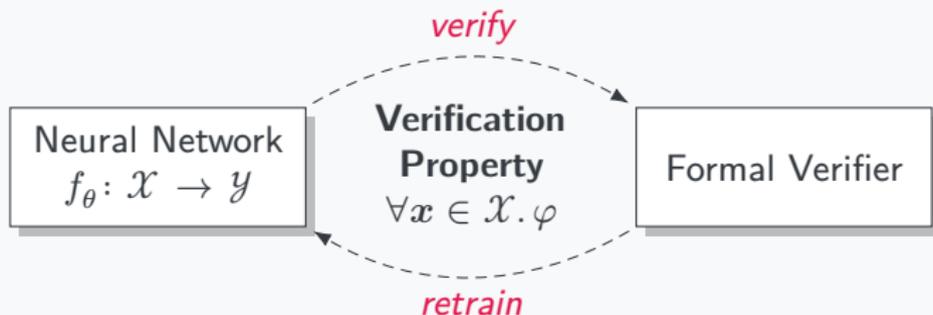


Figure: The continuous verification cycle.

Training Process:

1. translate φ into real-valued, differentiable loss $\llbracket \varphi \rrbracket$,
2. find a counterexample in \mathcal{X} (using gradient descent) that violates φ , and
3. add that counterexample to the training data.

Example

- **Constraint:** $\forall x \in \mathcal{X}. (5 \leq f(x) \wedge f(x) \leq 10)$
- **Translate:** e.g. using DL2³:

$$\llbracket a \leq b \rrbracket_{\text{DL2}} = \max(0, \llbracket a \rrbracket_{\text{DL2}} - \llbracket b \rrbracket_{\text{DL2}}) \text{ and}$$

$$\llbracket a \wedge b \rrbracket_{\text{DL2}} = \llbracket a \rrbracket_{\text{DL2}} + \llbracket b \rrbracket_{\text{DL2}}$$

$$\llbracket 5 \leq f(x) \wedge f(x) \leq 10 \rrbracket_{\text{DL2}}$$

$$\llbracket 5 \leq f(x) \rrbracket + \llbracket f(x) \leq 10 \rrbracket_{\text{DL2}}$$

$$\max(0, 5 - f(x)) + \max(0, f(x) - 10)$$

- **Find a counterexample:**

$$x^* = \max_{x' \in \mathcal{X}} \llbracket 5 \leq f(x) \wedge f(x) \leq 10 \rrbracket_{\text{DL2}}$$

- **Use counterexample in training.**

³M. Fischer et al. (2019). 'DL2: Training and Querying Neural Networks with Logic'. In: *Proceedings of the 36th International Conference on Machine Learning*.

Previous Work: Comparing Existing Differentiable Logics⁴

Logic	Domain	$\llbracket T \rrbracket$	$\llbracket F \rrbracket$	$\llbracket \neg x \rrbracket$	$\llbracket x \wedge y \rrbracket$	$\llbracket x \vee y \rrbracket$
DL2	$[0, \infty)$	0	∞	undefined	$x + y$	xy
Gödel	$[0, 1]$	1	0	$1 - x$	$\min(x, y)$	$\max(x, y)$

Research Question

How do existing differentiable logics (DLs) compare in terms of:

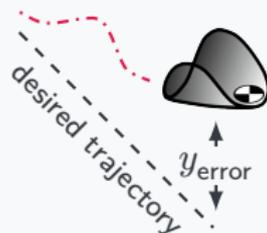
- gradients (learning behaviour)?
- logical consistency?
- establishing formal guarantees?

Findings

Training with *any* DL yields significantly improved *empirical* constraint satisfaction, but fails to provide (strong) formal guarantees.

⁴T. Flinkow, B. A. Pearlmutter et al. (2025). 'Comparing Differentiable Logics for Learning with Logical Constraints'. In: *Science of Computer Programming*. DOI: [10.1016/j.scico.2025.103280](https://doi.org/10.1016/j.scico.2025.103280).

Previous Work: Alsomitra Drone Controller⁵



(a) An *Alsomitra macrocarpa* seed. (b) The desired linear trajectory.

Constraint: *If the drone is above and close to the line, pitching down quickly and moving fast, the network should make it pitch up.*

Logic	RMSE	CAcc (%)	CSec (%)
Baseline	3.61×10^{-4}	0.00	0.00
DL2	1.23×10^{-3}	100.00	95.31
Fuzzy logic	1.16×10^{-3}	100.00	92.19

⁵C. Kessler et al. (2026). 'Neural Network Verification for Gliding Drone Control: A Case Study'. In: *AI Verification*. DOI: [10.1007/978-3-031-99991-8_9](https://doi.org/10.1007/978-3-031-99991-8_9).

Recent Work (in Progress): Strong(er) Formal Guarantees

Issues

- DL2 $\llbracket - \rrbracket_{\text{DL2}}: \Phi \rightarrow [0, \infty)$ loss is 0 if the constraint is satisfied.
- Consider the simple constraint $f(x) \leq 5$.
- $\llbracket a \leq b \rrbracket_{\text{DL2}} = \max(0, a - b)$ means gradients vanish once $a \leq b$.
- **Not *finding* a counterexample does not mean there is none!**

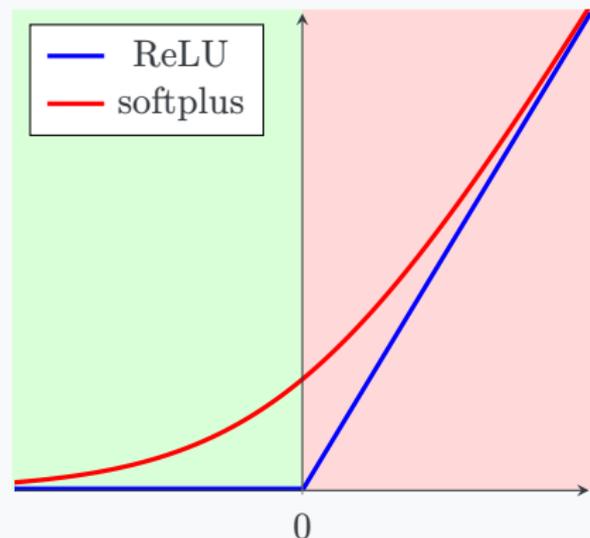
Ideas for a new differentiable logic

- Never let gradients vanish (i.e. make it *possible* to always find counterexamples)!
- Smooth connectives $\llbracket \wedge^s \rrbracket_{\text{Ours}}$ and $\llbracket \vee^s \rrbracket_{\text{Ours}}$ that approximate min and max as $s \rightarrow \infty$.

Non-vanishing Gradients Everywhere

Idea: even when a constraint is satisfied, provide a small gradient.

$$\llbracket a \leq b \rrbracket_{\text{DL2}} = \text{ReLU}(a - b) \quad \llbracket a \leq b \rrbracket_{\text{Ours}} = \text{softplus}(a - b)$$



Experimental Results



Constraint: *Predictions must be physically possible: the network should not predict two faces that are on opposite sides of the die.*

Logic	PAcc (%)	CAcc (%)	CSec (%)	Verified Accuracy (%) ^a		
				$\epsilon = 4/255$	$\epsilon = 8/255$	$\epsilon = 16/255$
Baseline	85.8	97.1	5.9	20.6	0.0 ⁽¹⁾	0.0
DL2	82.6	98.5	29.4	51.5 ⁽¹⁾	16.2 ⁽²⁾	1.5 ⁽¹⁾
Ours	78.9	100.0	100.0	100.0	100.0	91.2 ⁽⁵⁾

^a Superscript (^k) indicates the inputs that timed out and remain unknown.

Summary & Conclusion

1. Motivation

Correct-by-construction ML by specification-driven training.

2. Current Work

A differentiable logic with stronger formal guarantees.

3. Future Work

Stronger guarantees and more expressive specifications.

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Thank you! Any questions?

1. T. Flinkow, B. A. Pearlmutter et al. (2025). 'Comparing Differentiable Logics for Learning with Logical Constraints'. In: *Science of Computer Programming* 244, p. 103280. ISSN: 0167-6423. DOI: [10.1016/j.scico.2025.103280](https://doi.org/10.1016/j.scico.2025.103280)
2. T. Flinkow, M. Casadio et al. (2025). *A General Framework for Property-Driven Machine Learning*. DOI: [10.48550/arXiv.2505.00466](https://doi.org/10.48550/arXiv.2505.00466). arXiv: [2505.00466](https://arxiv.org/abs/2505.00466) [cs]