

# EFFICIENT NEURAL NETWORK ROBUSTNESS CERTIFICATION WITH GENERAL ACTIVATION FUNCTIONS

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# HOW GOOD IS YOUR NEURAL NETWORK ?



Pei, Kexin, et al. "Deepxplore: Automated whitebox testing of deep learning systems." *Proceedings of the 26th Symposium on Operating Systems Principles*. ACM, 2017.

# HOW GOOD IS YOUR NEURAL NETWORK ?

- Neural networks are not robust to input perturbations.
- **Pushing the limit: One Pixel Attack !**
  - Su et. al. "One pixel attack for fooling deep neural networks." IEEE Transactions on Evolutionary Computation (2019).
- **Conclusion:** There is a need for an **automated** and **scalable** analysis to certify realistic neural networks against such input perturbations.



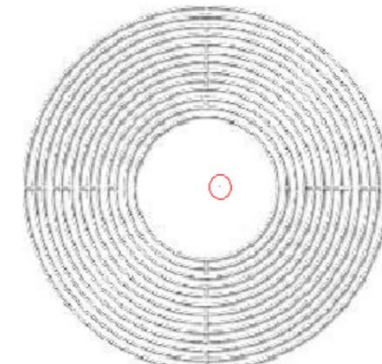
Planetarium  
Mosque(7.81%)



Comforter  
Pillow(6.83%)

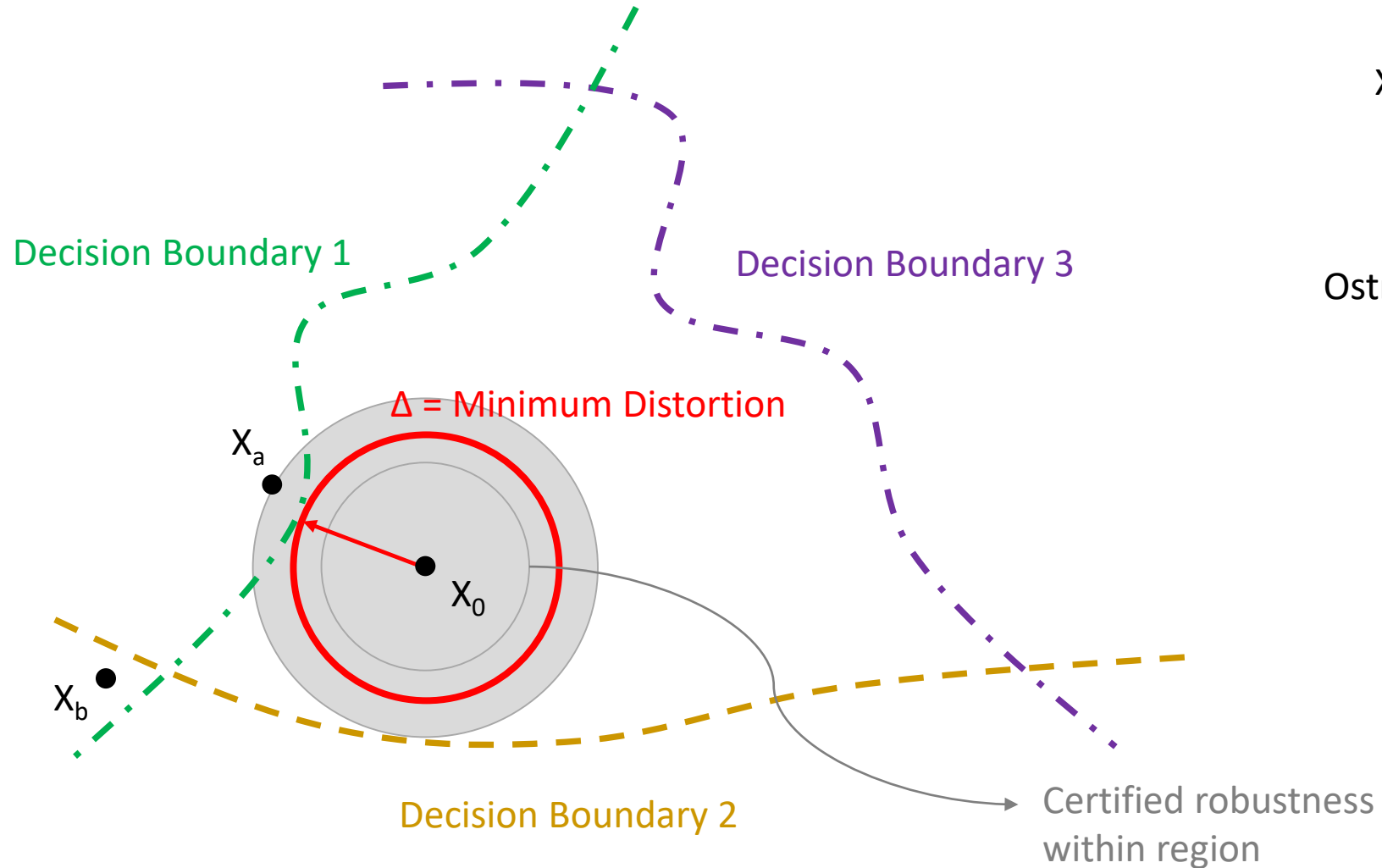


Jellyfish  
Bathing tub(21.18%)



Whorl  
Blower (37.00%)

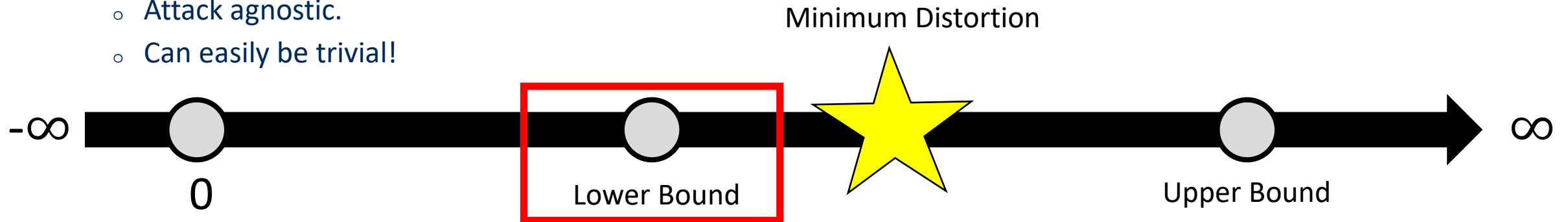
# HOW TO CERTIFY NEURAL NETWORKS ?



|         |        |       |
|---------|--------|-------|
| $X_0$   | $X_a$  | $X_b$ |
| Ostrich | Vacuum | Shoe  |

# HOW TO CERTIFY NEURAL NETWORKS ?

- **Upper bounds** on minimum distortion:
  - Attack dependent.
  - Is pretty non-informative in case of weak attacks that fail often.
- Formal Verification, **exact** minimum distortion:
  - NP-hard.
- **Lower bounds** on minimum distortion:
  - Attack agnostic.
  - Can easily be trivial!

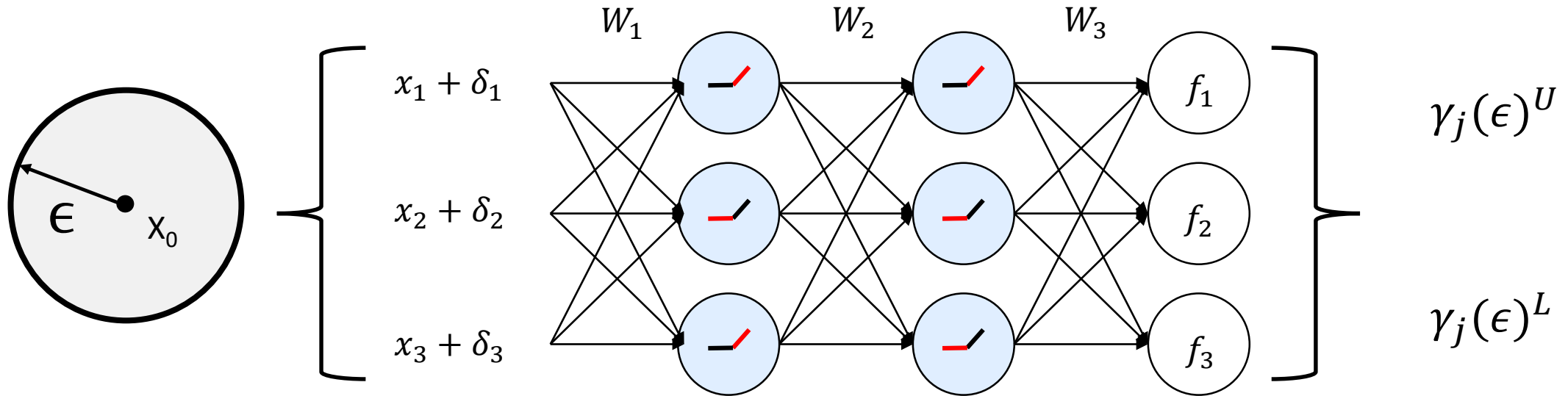


# FAVORABLE PROPERTIES OF CERTIFICATION METHODS

Table 1: Comparison of methods for providing adversarial robustness certification in NNs.

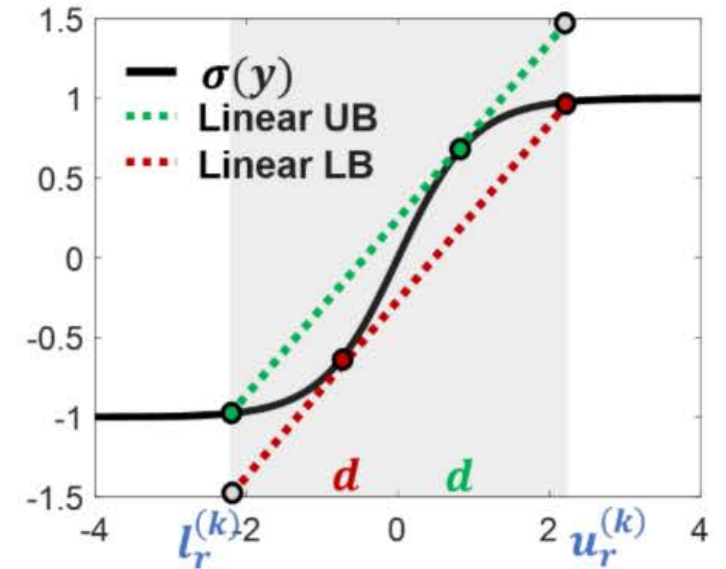
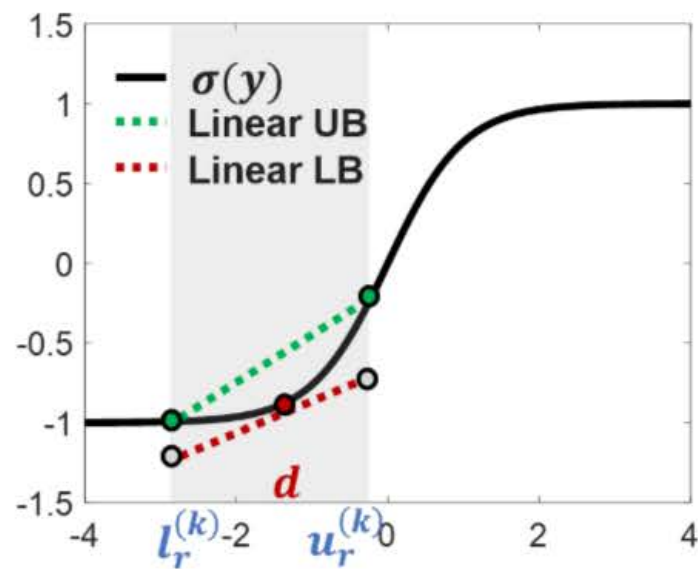
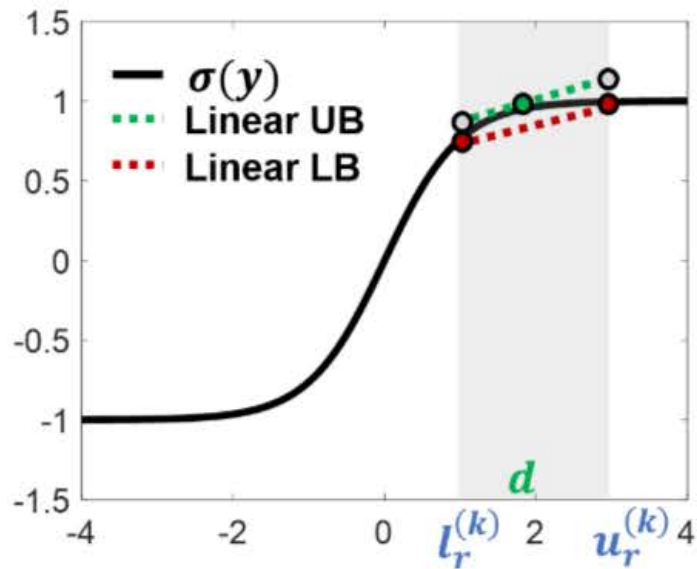
| Method                     | Non-trivial bound | Multi-layer | Scalability | Beyond ReLU     |
|----------------------------|-------------------|-------------|-------------|-----------------|
| Szegedy et. al. [3]        | ×                 | ✓           | ✓           | ✓               |
| Reluplex [15], Planet [25] | ✓                 | ✓           | ×           | ×               |
| Hein & Andriushchenko [26] | ✓                 | ×           | ✓           | differentiable* |
| Raghunathan et al. [19]    | ✓                 | ×           | ×           | ×               |
| Kolter and Wong [18]       | ✓                 | ✓           | ✓           | ×               |
| Fast-lin / Fast-lip [20]   | ✓                 | ✓           | ✓           | ×               |
| CROWN (ours)               | ✓                 | ✓           | ✓           | ✓ (general)     |

# STEP 1: EXPLICIT OUTPUT BOUNDS



# LINEAR L/U BOUNDS FOR GENERAL ACTIVATION FUNCTIONS

- **Keyword:** Adaptive!

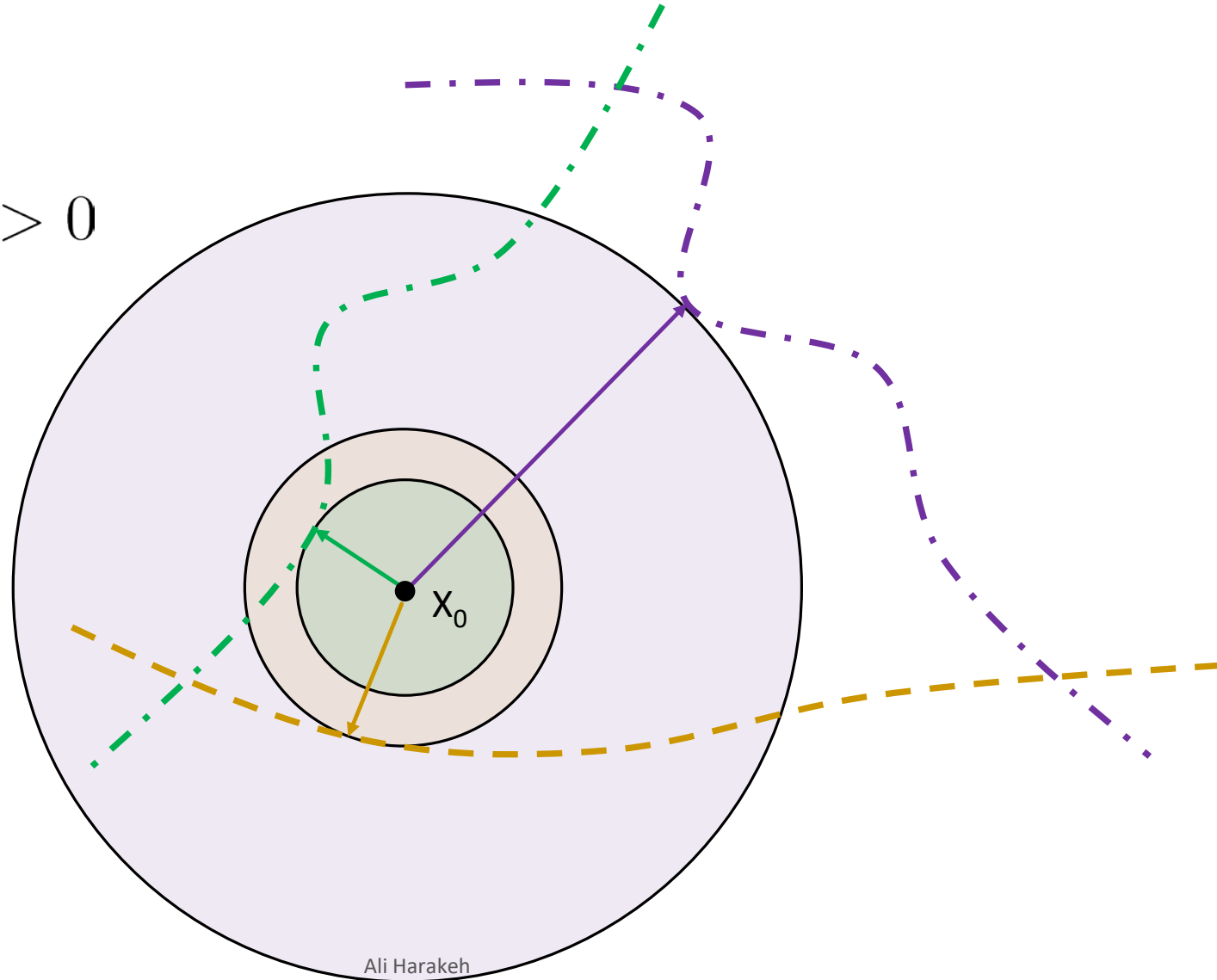




## STEP 2: CERTIFIED LOWER BOUND FOR MINIMUM DISTORTION

$$\hat{\epsilon}_t = \max_{\epsilon} \epsilon$$
$$s.t. \gamma_c^L(\epsilon) - \gamma_t^U(\epsilon) > 0$$

$$\hat{\epsilon} = \min_{t \neq c} \hat{\epsilon}_t$$



# RESULTS: TIGHTER LOWER BOUNDS

Table 4: Comparison of certified lower bounds on large ReLU networks. Bounds are the average over 100 images (skipped misclassified images) with random attack targets. Percentage improvements are calculated against Fast-Lin as Fast-Lip is worse than Fast-Lin.

| Network                       | Certified Bounds |          |          |                | Improvement (%)       | Average Computation Time (sec) |          |           |
|-------------------------------|------------------|----------|----------|----------------|-----------------------|--------------------------------|----------|-----------|
|                               | $l_p$ norm       | Fast-Lin | Fast-Lip | CROWN-Ada      | CROWN-Ada vs Fast-Lin | Fast-Lin                       | Fast-Lip | CROWN-Ada |
| MNIST<br>$4 \times [1024]$    | $l_1$            | 1.57649  | 0.72800  | <b>1.88217</b> | +19%                  | 1.80                           | 2.04     | 3.54      |
|                               | $l_2$            | 0.18891  | 0.06487  | <b>0.22811</b> | +21%                  | 1.78                           | 1.96     | 3.79      |
|                               | $l_\infty$       | 0.00823  | 0.00264  | <b>0.00997</b> | +21%                  | 1.53                           | 2.17     | 3.57      |
| CIFAR-10<br>$7 \times [1024]$ | $l_1$            | 0.86468  | 0.09239  | <b>1.09067</b> | +26%                  | 13.21                          | 19.76    | 22.43     |
|                               | $l_2$            | 0.05937  | 0.00407  | <b>0.07496</b> | +26%                  | 12.57                          | 18.71    | 21.82     |
|                               | $l_\infty$       | 0.00134  | 0.00008  | <b>0.00169</b> | +26%                  | 8.98                           | 20.34    | 16.66     |

Table 5: Comparison of certified lower bounds by CROWN-Ada on ReLU networks and CROWN-general on networks with tanh, sigmoid and arctan activations. CIFAR models with sigmoid activations achieve much worse accuracy than other networks and are thus excluded.

| Network                       | Certified Bounds by CROWN-Ada and CROWN-general |         |         |         |         | Average Computation Time (sec) |       |         |        |
|-------------------------------|---|---------|---------|---------|---------|--------------------------------|-------|---------|--------|
|                               | $l_p$ norm                                      | ReLU    | tanh    | sigmoid | arctan  | ReLU                           | tanh  | sigmoid | arctan |
| MNIST<br>$3 \times [1024]$    | $l_1$   | 3.00231 | 2.48407 | 2.94239 | 2.33246 | 1.25                           | 1.61  | 1.68    | 1.70   |
|                               | $l_2$   | 0.50841 | 0.27287 | 0.44471 | 0.30345 | 1.26                           | 1.76  | 1.61    | 1.75   |
|                               | $l_\infty$                                      | 0.02576 | 0.01182 | 0.02122 | 0.01363 | 1.37                           | 1.78  | 1.76    | 1.77   |
| CIFAR-10<br>$6 \times [2048]$ | $l_1$   | 0.91201 | 0.44059 | -       | 0.46198 | 71.62                          | 89.77 | -       | 83.80  |
|                               | $l_2$   | 0.05245 | 0.02538 | -       | 0.02515 | 71.51                          | 84.22 | -       | 83.12  |
|                               | $l_\infty$                                      | 0.00114 | 0.00055 | -       | 0.00055 | 49.28                          | 59.72 | -       | 58.04  |

# CROWN: WEAK POINTS

1. Feed-Forward Neural Networks with fully connected layers only.
  - CNN-Cert: <https://arxiv.org/abs/1811.12395>
2. Input should be in the form of an epsilon bound norm ball.
  - Usually not an issue. Common assumption.
3. Single input certification. Results averaged over 100 points of input.
  - A2I and derivatives? Covering arguments?

## DISCUSSION QUESTIONS

What do you think of the provided comparison method?

Do you think the authors overpromise scalability?

Can we argue safety of a DNN using CROWN?