Certifiable Neural Networks

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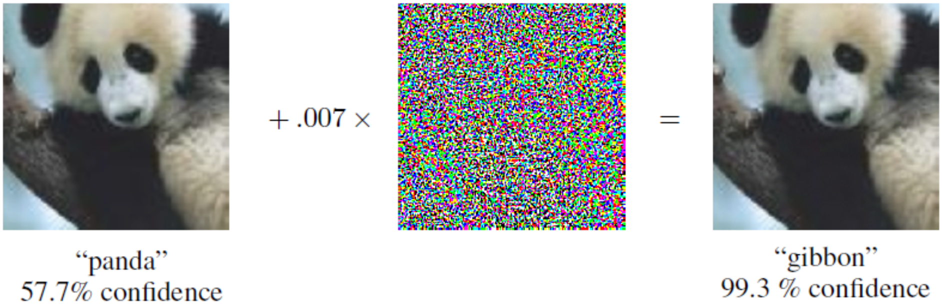
Publications (discussed here):

- ICML'18 - Differentiable Abstract Interpretation for Provably Robust Neural Networks (DiffAI)
- ICLR'20 - Universal Approximation with Certified Networks
- NeurIPS'18 - Fast and Effective Robustness Certification (ERAN)
- S&P'18 - AI2: Safety and Robustness Certification of Neural Networks with Abstract Interpretation

Motivation - Adversarial Attacks



Example of FGSM attack produced by Goodfellow et al. (2014)

Overview of Neural Network Safety

Identifying vulnerability

Adversarial attacks: Goodfellow et al. (2014)

Reducing vulnerability

Adversarial training: Madry et al. (2018)

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Robustness certification: AI2, ERAN

Increasing certifiable invulnerability

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Increasing certifiable invulnerability

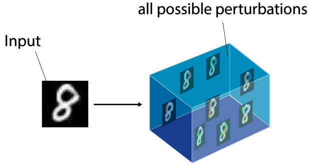
Certifiable training: DiffAI

AI2 - First scalable verifier for neural networks.

DiffAI - First scalable framework for certifiable training.

Preliminary Property - L_∞ Adversarial Ball

Many developed attacks: Goodfellow et al. (2014); Madry et al. (2018); Evtimov et al. (2017); Athalye & Sutskever (2017); Papernot et al. (2017); Xiao et al. (2018); Carlini & Wagner (2017); Yuan et al. (2017); Tramèr et al. (2017)



$$\mathrm{Ball}_\epsilon(input) = \{attack \mid \|input - attack\|_\infty \leqslant \epsilon\}$$

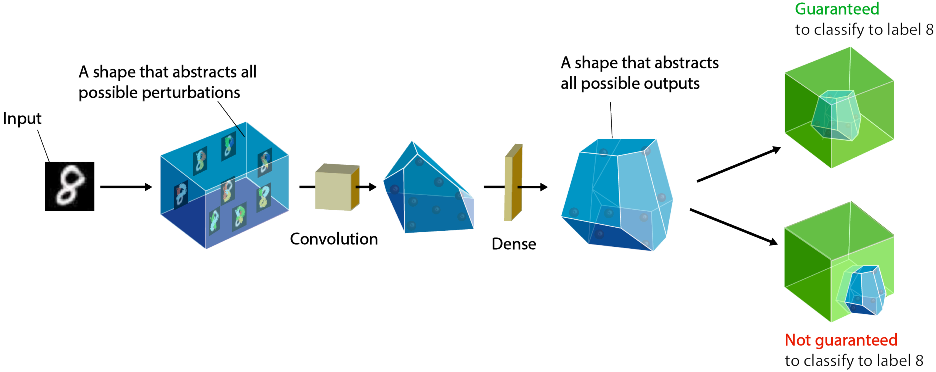
A net is *ϵ-robust* at x if it classifies every example in $\mathrm{Ball}_\epsilon(x)$ the same and correctly

Certification

Robustness Certification

Verification: Prove that a network is ϵ-robust at a point

Abstract Interpretation: certify by over-approximation [Cousot & Cousot (1977)]



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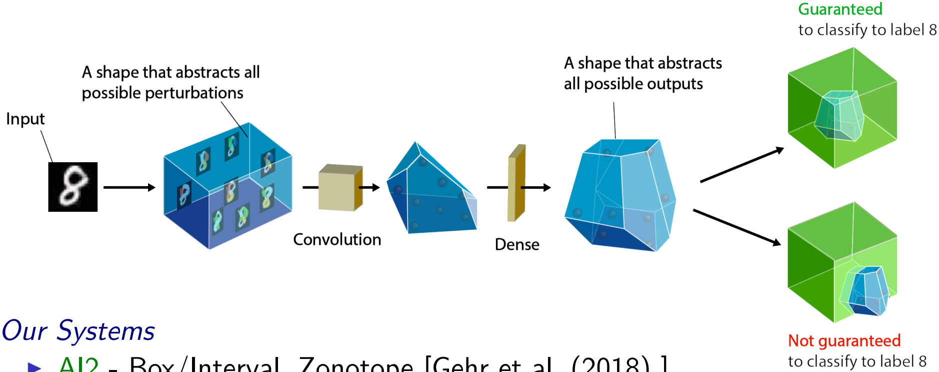

Our Systems

- AI2 - Box/Interval, Zonotope [Gehr et al. (2018)]
- DiffAI - HybridZono, zBox, zDiag, zSwitch, zSmooth [Mirman et al. (2018)]
- ERAN - DeepZono [Singh et al. (2018)]

Image Credit: Petar Tsankov

Abstract Interpretation

Cousot & Cousot (1977)

Abstract Interpretation is heavily used in industrial large-scale program analysis to compute over-approximation of program behaviors [1]

Provide

- domain $\mathcal{D}$ of abstract objects d
- concretization function $\gamma : \mathcal{D} \to \mathcal{P}(\mathbb{R}^n)$
- concrete function $f : \mathbb{R}^n \to \mathbb{R}^n$

Develop a sound transformer $f^{\#} : \mathcal{D} \to \mathcal{D}$

[1] For example by Astrée: Blanchet et al. (2003)

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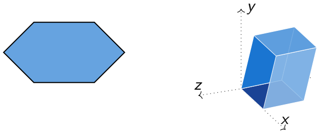


Zonotope Domain

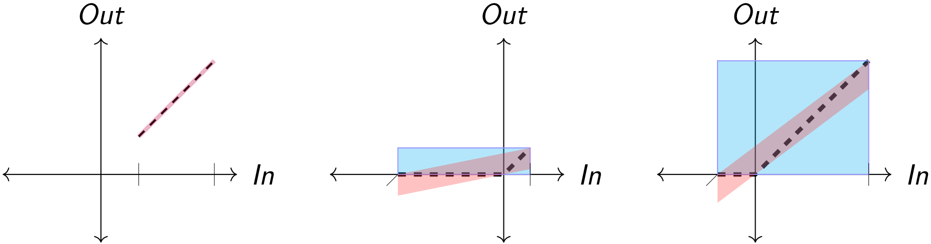
- Affine transform of k-cube onto p dims
- Ball$_\epsilon$: perfect
- $(\cdot M)^{\#}$: perfect
- ReLU$^{\#}$: zBox, zDiag, DeepZono

[1] For example by Astrée: Blanchet et al. (2003)

Zonotope Domain

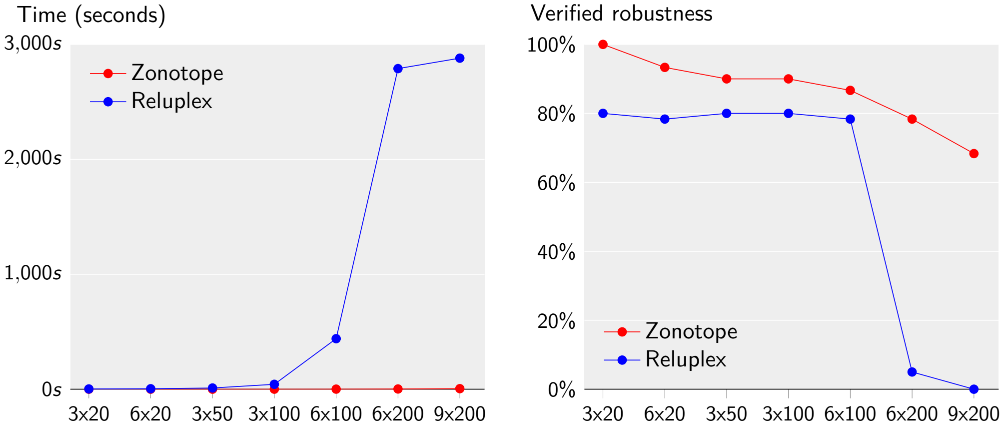
Example ReLU Transformers for Zonotope

Examples of zBox (blue) and DeepZono (red) for approximating $Out = ReLU(In)$ (dashed line).



- zBox: Treat as Box when surrounding zero
- DeepZono: Minimize area in In/Out plane.

AI2 Certification Results



Comparison to Reluplex, Katz et al. (2017), on small feed-forward networks for MNIST.

Training

Reducing Vulnerability

Certification Caveat

- Neural networks aren't robust by default.
- Why try to certify non-robust networks?

Adversarial Training

Defense: Train a network so that *most* inputs are *mostly* robust.

- Madry et al. (2018); Tramèr et al. (2017); Cisse et al. (2017); Yuan et al. (2017)

Certifiable Training

- Experimentally robust nets not necessarily *certifiably* robust
- Intuition: not all correct programs are easily provable

Certifiable Training

Train a Network to be *Certifiably* Robust[2]

Given:

- Net_θ with weights θ
- Training inputs and labels

Find:

- θ that maximizes number of inputs we can *certify* are ϵ-robust

[2] Also addressed by: Raghunathan et al. (2018); Kolter & Wong (2017); Dvijotham et al. (2018)

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Method

- Design a loss function based on certification goal
- Differentiate through certifier
- Perform SGD

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Scalability
CIFAR10

			Time to Train 1 Epoch	
Model	#Neurons	#Weights	Baseline	DiffAI
SkipNet-18[3]	∼558k	∼16mill	152s	260s

- Can use a less precise domain for training than for certification
- Can test and train with larger nets than prior work

[3]like that described by He et al. (2016) but without pooling or dropout.

Robustness Provability

CIFAR10 with $\epsilon = 0.012$ [4]

Training Method	%Certified DeepZono
Baseline	0
Adversarial	7
DiffAI	64

- Significantly increases provability with scalable verifiers.
- For small ϵ we lose little accuracy.

[4] Numbers from Singh et al. (2018) on 100 test images

The Gap

The state of the art still far from goal

- Balunovic & Vechev (2019) gets 60.5% certified robustness and 78.4% accuracy on CIFAR10 with $\epsilon = \frac{2}{255}$
- Standard training $>$ 95% accuracy.

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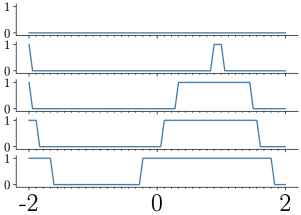
They provably exist![5]



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Universal Approximation with Certified Networks

Universal Interval-Certified Approximation

Let $\Gamma \subset \mathbb{R}^m$ be a compact set and let $f : \Gamma \to \mathbb{R}$ be a continuous function. For all $\delta > 0$, there exists a ReLU network n such that for all boxes $[a, b]$ in Γ defined by points $a, b \in \Gamma$ where $a_k \leq b_k$ for all k, the propagation of the box $[a, b]$ using interval analysis through the network n, denoted $n^\sharp([a, b])$, approximates the set $[l, u] = [\min f([a, b]), \max f([a, b])] \subseteq \mathbb{R}$ up to δ,

$$[l + \delta, u - \delta] \subseteq n^\sharp([a, b]) \subseteq [l - \delta, u + \delta]$$

tldr: univeral approximation can be lifted to nets that are certifiably robust with *Box*.

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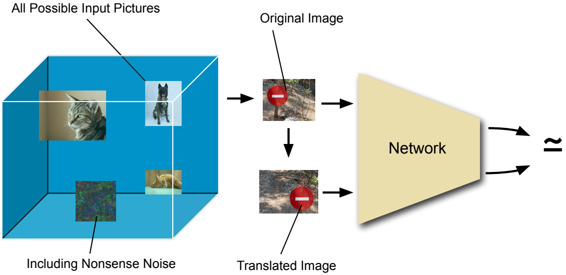
Future Work

Describe lower & upper bounds on size/depth/width with certifiable networks

Beyond Local Robustness

Network Invariants (Future Work)

- Verify properties across every possible input.
- Invariance to translations, rotations, arbitrary perturbations.



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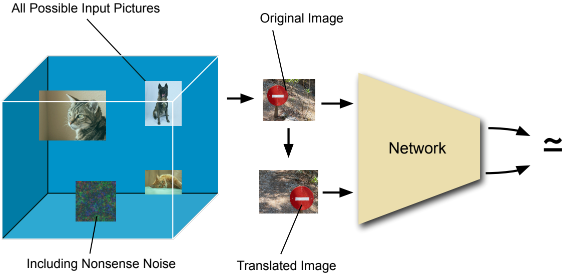

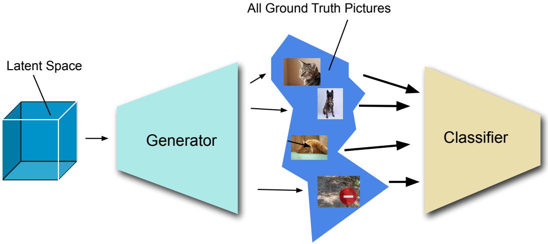

Generative Specifications (Ongoing)

Specify input with generative models [Mirman et al. (2020)]

Generative Specifications

- Generative specifications are necessarily non-convex.
- Feasible Restriction: Interpolative Specifications

Our Work

certify images from interpolations in
the generative model's latent space

Convex Relaxation Analysis

analyzes non-realistic images
from pixel-wise interpolation

Conclusion

First scalable certification framework

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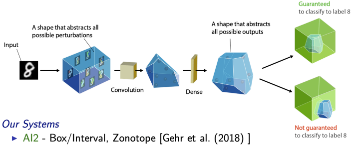

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Existence of interval provable nets

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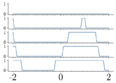

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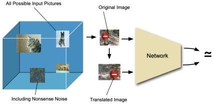

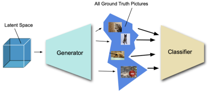

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