#### **Certify or Predict: Boosting Certified Robustness with Compositional Architectures**



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#### **Adversarial Examples**



Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." *arXiv preprint arXiv:1412.6572* (2014).

## Neural Network Verification

Robustness property:

 $argmax_i \ h(x)_i = argmax_i \ h(x')_i$  $\forall x' \in B_{\epsilon}^{\infty}(x)$ 



## Problem Statement

- Adversarial accuracy requires increased network capacity
- Verification gets increasingly difficult with network depth
- ➔ Small, provably trained networks have low standard accuracy
- → ACE: Compose networks with different strengths



## ACE – Compositional Architecture

- For every sample decide whether to use core- or certification-network
- Key components:
  - Deep standard network
  - Shallow provable network
  - Selection mechanism
    - Train network to predict certification difficulty
    - Evaluate certification network entropy



### **Effectiveness of Selection**

- Strong separation of samples based on certifiability
- Significantly increased accuracy of the certification-network on the selected sample subset



# ACE Results

- Significant reduction in certified accuracy loss, for gains in natural accuracy
- Effect observed across:
  - Network architectures
  - Perturbation sizes
  - Datasets
  - Certification and training methods



Balunovic, Mislav, and Martin Vechev. "Adversarial training and provable defenses: Bridging the gap." *ICLR* 2019 Zhang, Huan, et al. "Towards stable and efficient training of verifiably robust neural networks." *arXiv:1906.06316* 2019 Xu, Kaidi, et al. "Automatic perturbation analysis for scalable certified robustness and beyond." NIPS 2020

### Thank you for your attention!

#### Paper and Code:

https://www.sri.inf.ethz.ch/publications/mueller2021boosting



#### Poster Session 10