# Exploiting Label Similarity to Enhance Verifiable Robust Classifiers

#### Shiqi Wang

Columbia University tcwangshiqi@cs.columbia.edu

#### Kevin Eykholt, Taesung Lee, Jiyong Jang, Ian Molloy **IBM Research**

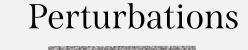
Cyber Security Intelligence Group

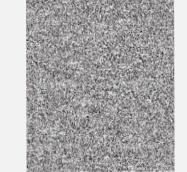
## \* Adversarial Examples & Verifiable Training

### Adversarial examples: Minor perturbations will cause mispredictions

+







**Interval Analysis:** Verify the absence of adversarial examples ReLU(-x+5y)

Input: x∈[4,6] & y∈[1,5]; Linear layer:  $-x+5y \in [-1,16]$ ReLU layer: ReLU(-x+5y)  $\in$  [0,16] Output layer: Cat-Dog $\in$ [0,16]>0?

Verifiable Training: Training networks with verification methods to learn provable robustness guarantee against adversarial examples.

Even SOTA verifiable training **CROWN-IBP**[1] has very poor performance. For instance with CIFAR10,  $L_{\infty} \leq 8/255$ :

46% clean accuracy & 33% verified accuracy

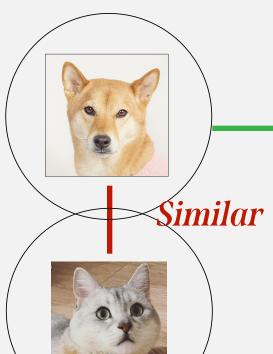
# \* Insight of Our Work: Label Similarity!

Main limitation: a single robustness distance for all classes=> The maximal distance of the robustness is limited by similar labels:

[Similar] Cats vs Dogs: 29% clean accuracy

[Dissimilar] Cats vs Cars: 56% clean accuracy

### Adaptive robustness accounting for label similarity!



#### Dissimilar

Dogs vs Cars: Dissimilar => Able to learn **large** robustness distance

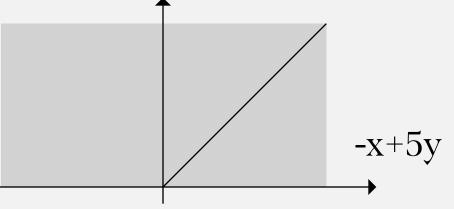
Cats vs Dogs: Similar => Only tolerate **small** robustness distance





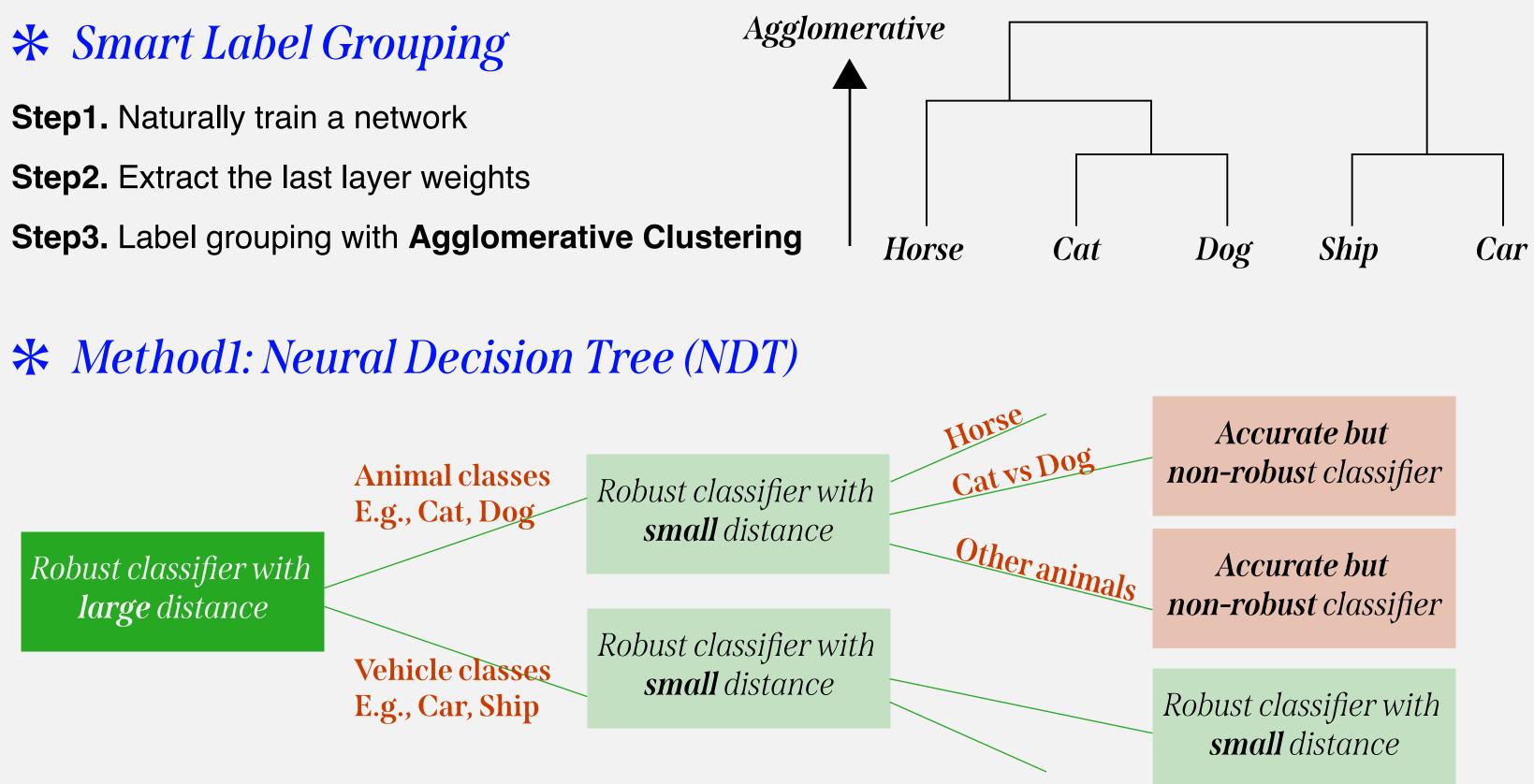
Misclassify to Dog







**Step1.** Naturally train a network **Step2.** Extract the last layer weights



# \* Method2: Inter-Group Robustness Prioritization (IGRP)

 $L_{IGRP} = L_{inner} + L_{outer}$ 

Inner loss: similar classes & small distance **Outer loss: dissimilar classes & large distance** For instance, true label is Cat Small distance logits range [I, u] Large distance logits range [l', u']

