Shallow-Deep Networks: Understanding and Mitigating Network Overthinking

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ICML 2019 - Long Beach, CA

MARYLAND CYBERSECURITY CENTER

What is overthinking?

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i. Wastes our valuable energy (**wasteful**)
ii. Causes us to make mistakes (**destructive**)

Do deep neural networks overthink too?

Without requiring the full depth, DNNs can correctly classify the majority of samples.

Experiments on four recent CNNs and three common image classification tasks

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i. Wastes computation for up to **95%** of the samples (**wasteful**)
ii. Occurs in **~50%** of all misclassifications (**destructive**)

How do we detect overthinking?

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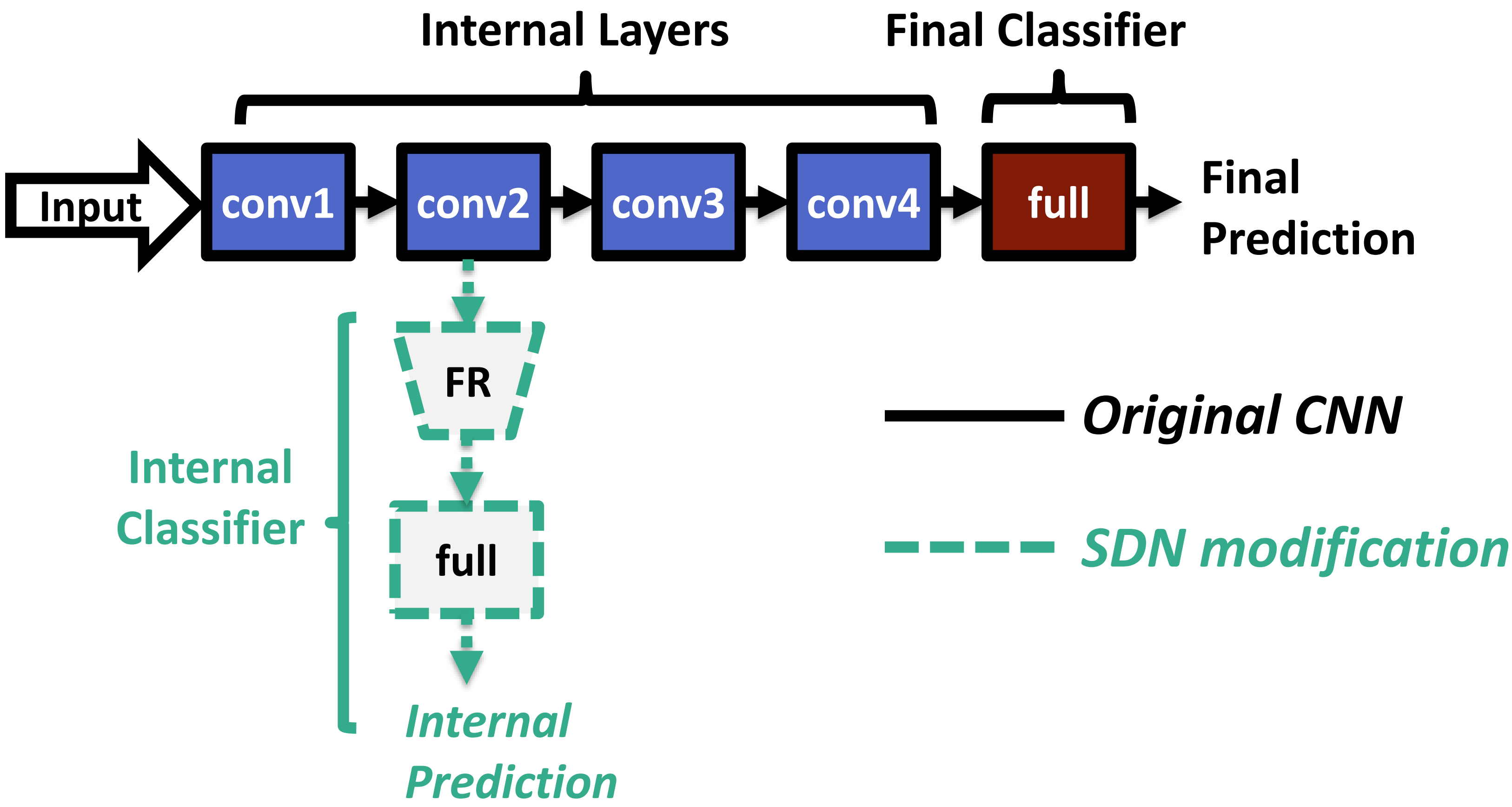
- Our generic **Shallow-Deep Network (SDN)** modification introduces internal classifiers to *DNNs.*

The SDN modification



Applied to *VGG, ResNet, WideResNet* and *MobileNet.*

The SDN modification

Challenge

How to train accurate internal classifiers?

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Prior Work

Claims this hurts the accuracy in *off-the-shelf* DNNs

Proposes a *unique* architecture[1]

[1] Huang, Gao, et al. "Multi-scale dense convolutional networks for efficient prediction." *ICLR 2018*

The SDN modification

Challenge

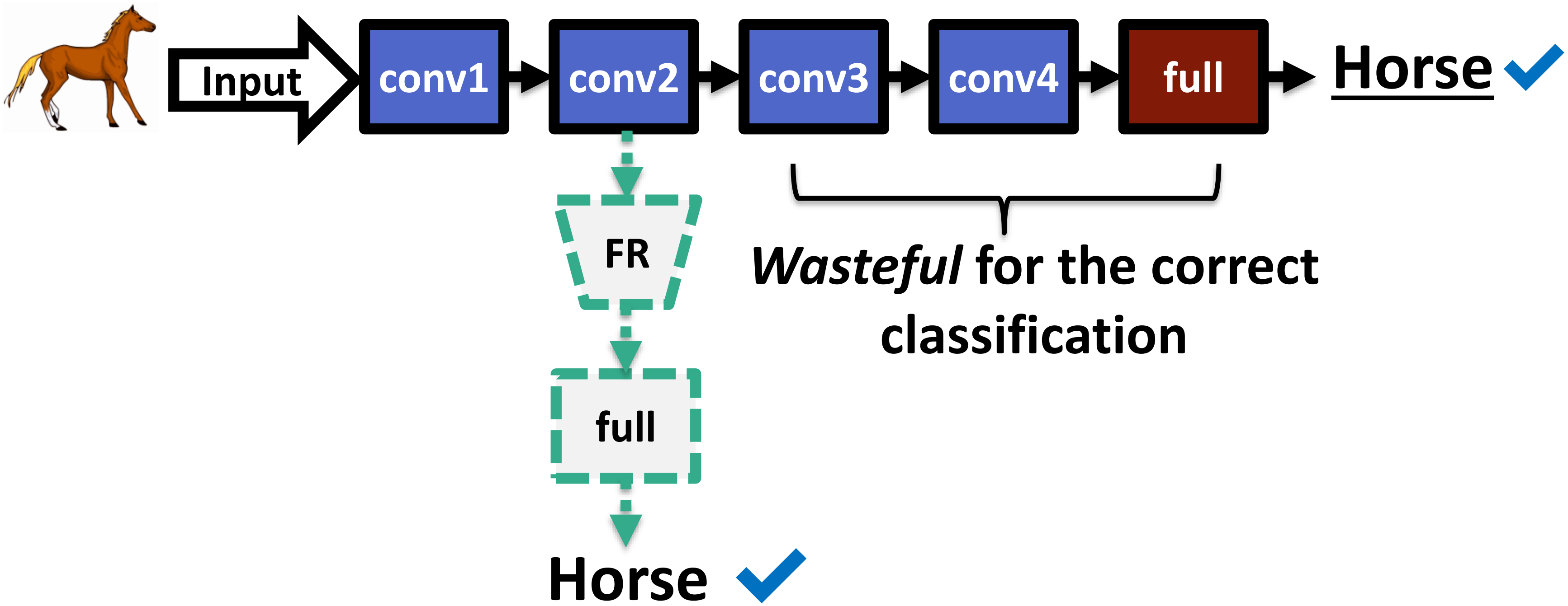
How to train accurate internal classifiers?

Results

Our modification often *improves* the original accuracy by up to **10%**.

(**See our poster**)

The wasteful effect of overthinking



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Challenge

How can we know where in the DNN to stop?

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Our Solution

Classification confidence of the internal classifiers

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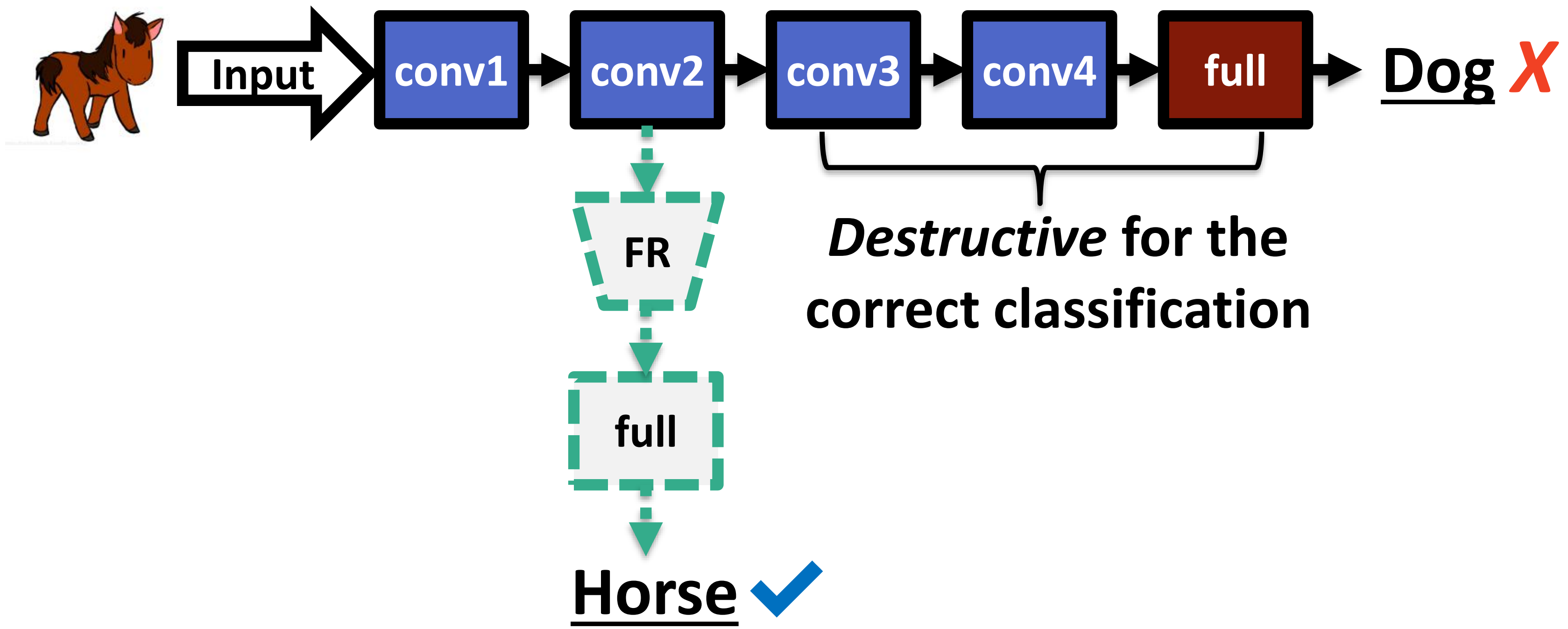
Results

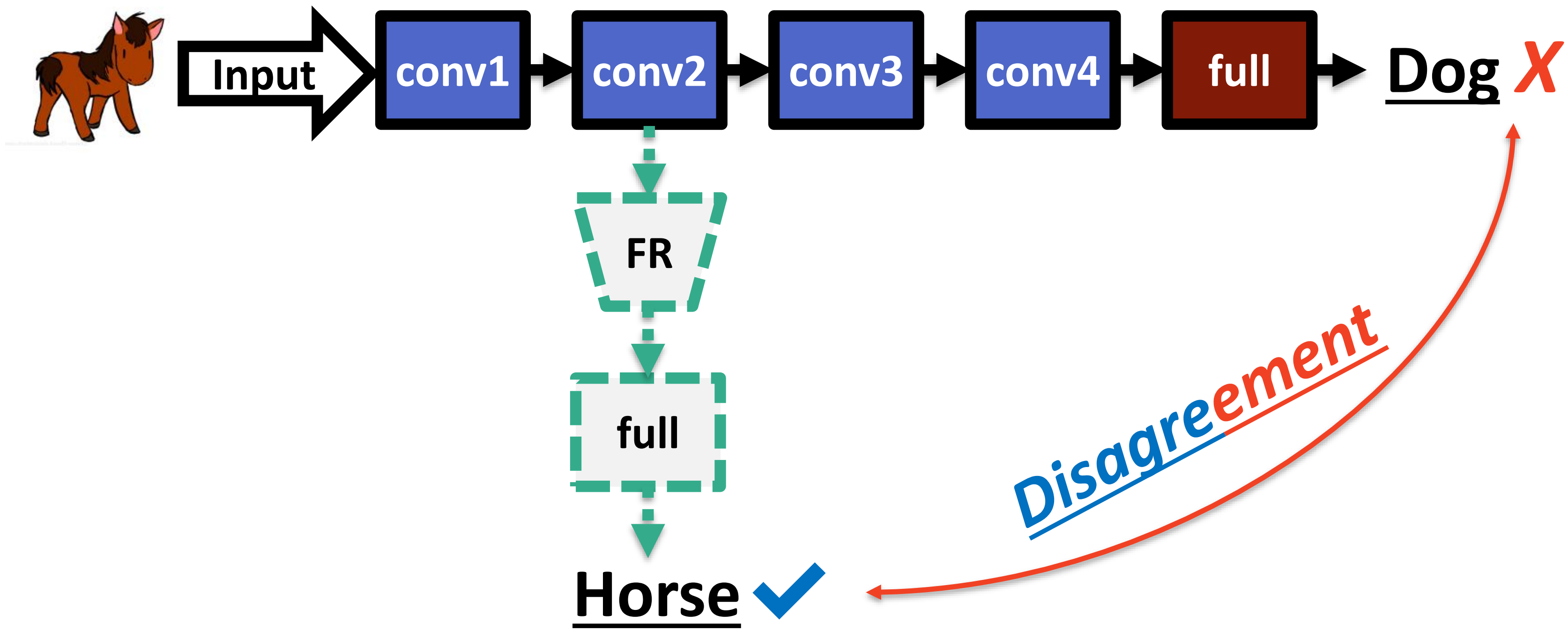
A *confidence-based early exit scheme* reduces the average inference cost by up to **50%**.

(**See our poster**)

The destructive effect of overthinking



The destructive effect causes disagreement



The destructive effect causes disagreement

Challenge

How can we quantify the internal disagreement?

Our Solution

The *confusion* metric

The destructive effect causes disagreement

<u>Our Solution</u>

The confusion metric

<u>Results</u>

Confusion indicates *whether a misclassification is likely.*

Confusion is a *reliable error indicator.*

(**See our poster**)

The destructive effect causes disagreement

Our Solution

The confusion metric

Results

Backdoor attacks [2] also increase the confusion of the victim DNN for malicious samples.

(**See our poster**)

[2] Gu, Tianyu, et al. "BadNets: Evaluating Backdooring Attacks on Deep Neural Networks." *IEEE Access* 7 (2019): 47230-47244.

Implications

- Eliminating overthinking would lead to *a significant boost* in accuracy and inference-time.

- We need DNNs that can *adjust their complexity* based on the required feature complexity.

For more details, visit our website

http://shallowdeep.network

Thank you!

Don't overthink! Come and see our poster!

Pacific Ballroom – Poster #24 – 06:30-09:00 PM