

# A Low-cost Fault Corrector for Deep Neural Networks through Range Restriction

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**IOWA**

# DNNs are increasingly deployed in safety-critical domains



*But do they always provide high-fidelity output?*

# No, thanks to Soft Errors

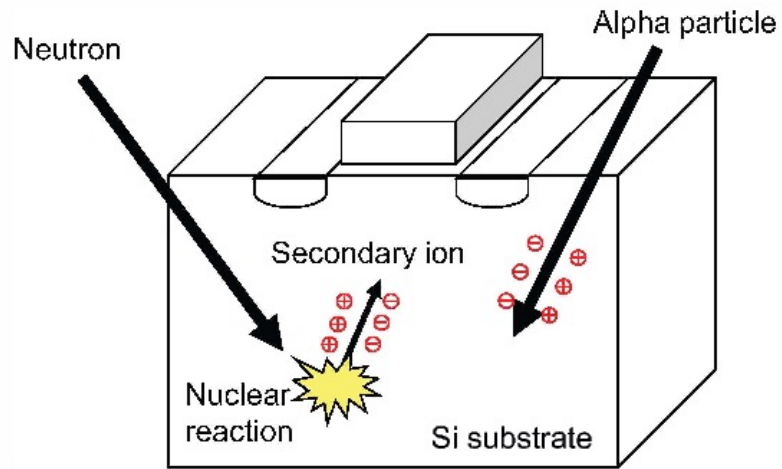
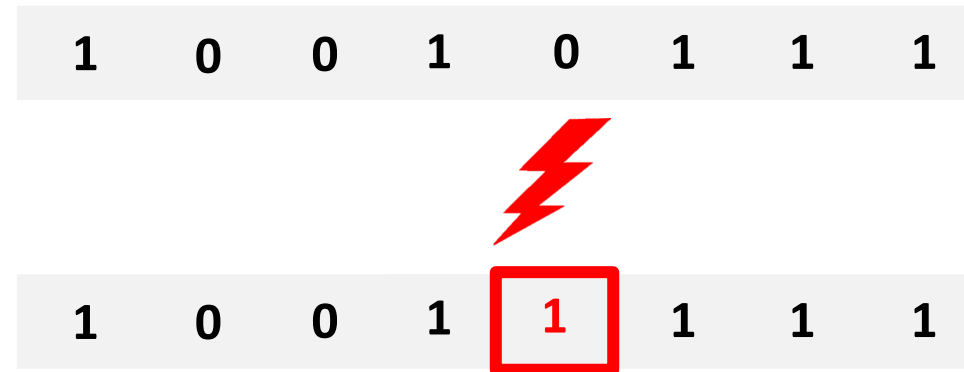


Fig. 3. Soft error mechanism due to neutron and alpha.



# Silent data corruptions (SDCs)



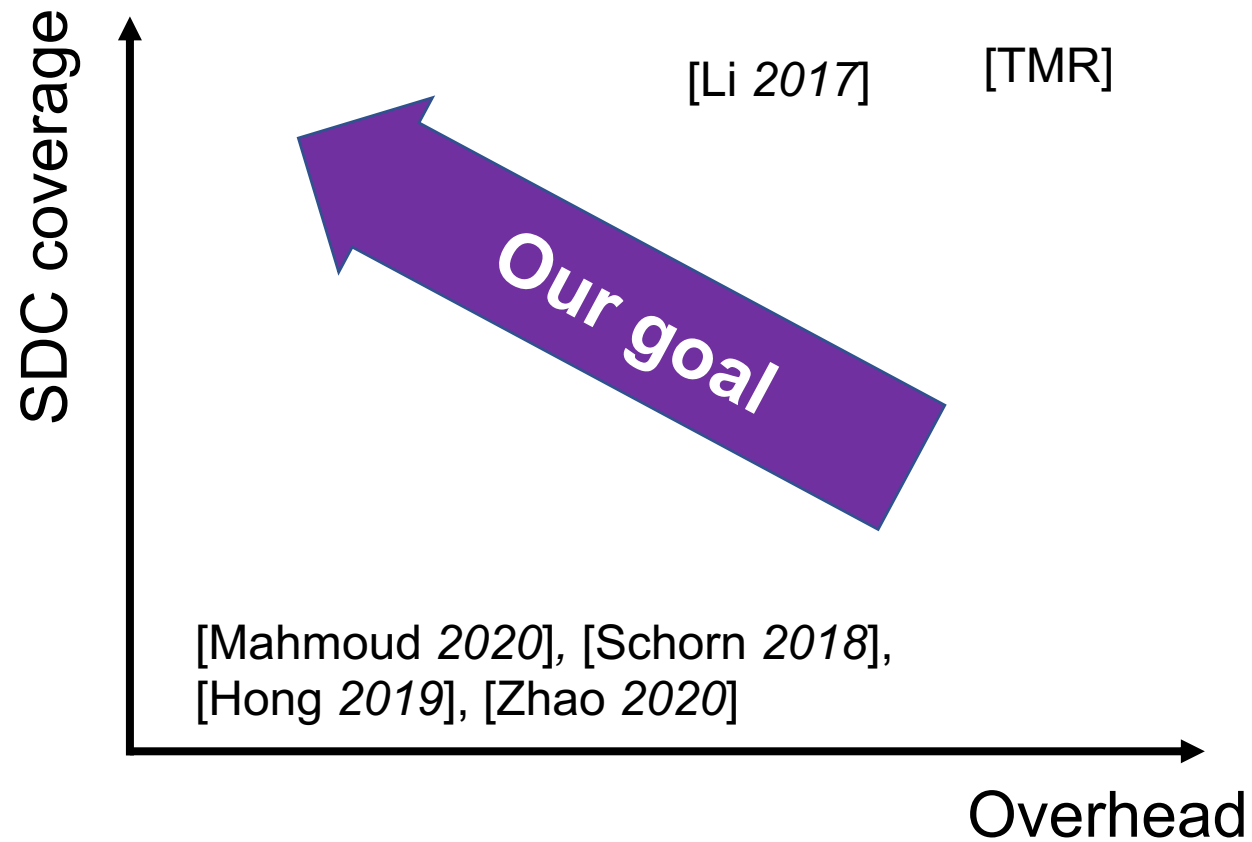
Prediction (without fault):  
**156.58°**



Prediction (**with** fault):  
**-78.09°**

**We need effective solution to mitigate SDCs**

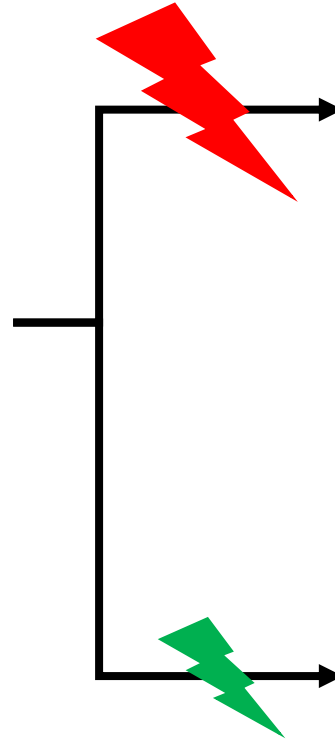
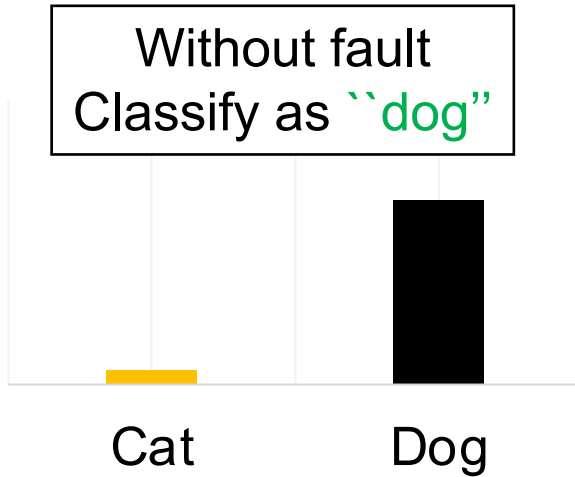
# Towards reliable DNNs



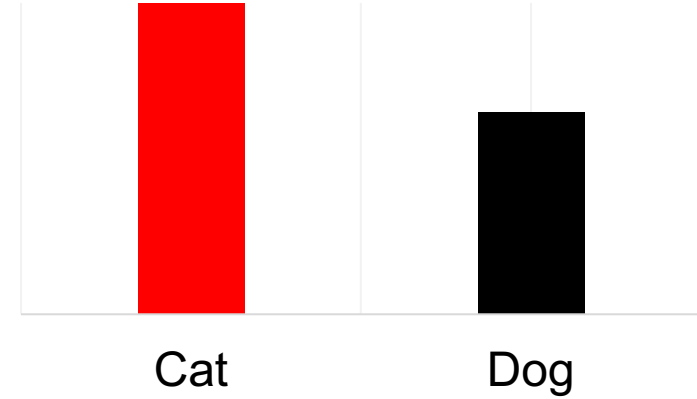
# DNNs can be **unreliable**



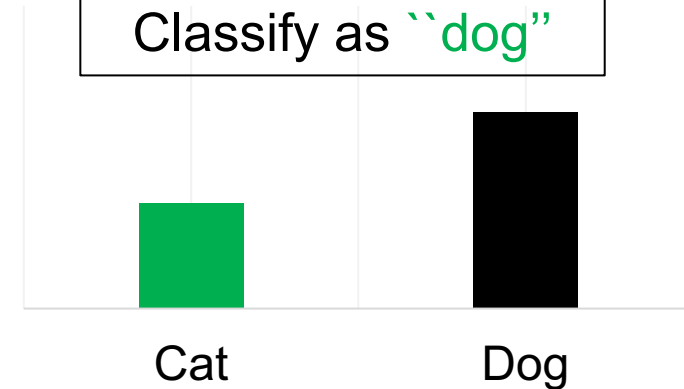
Output score



With **critical** fault  
Classify as ``cat``

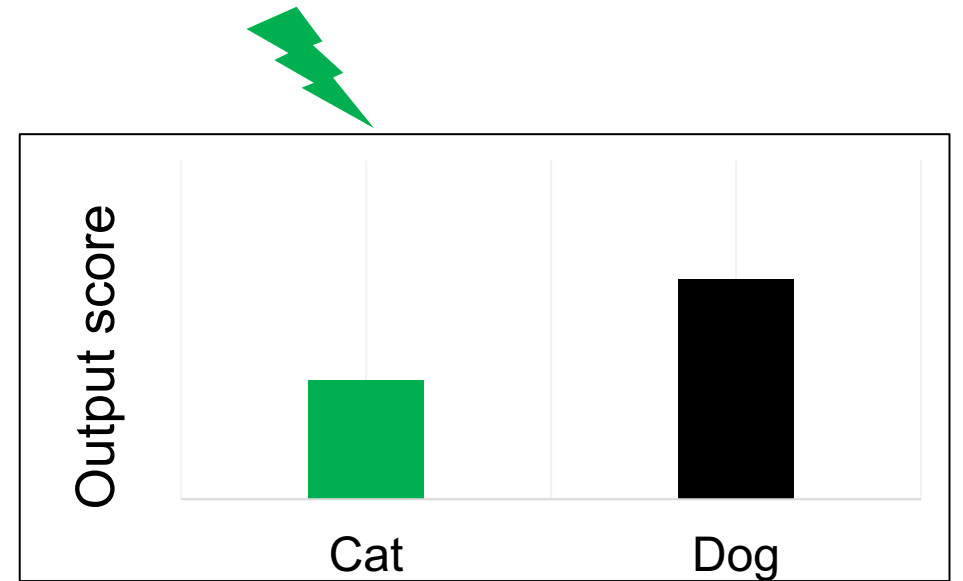
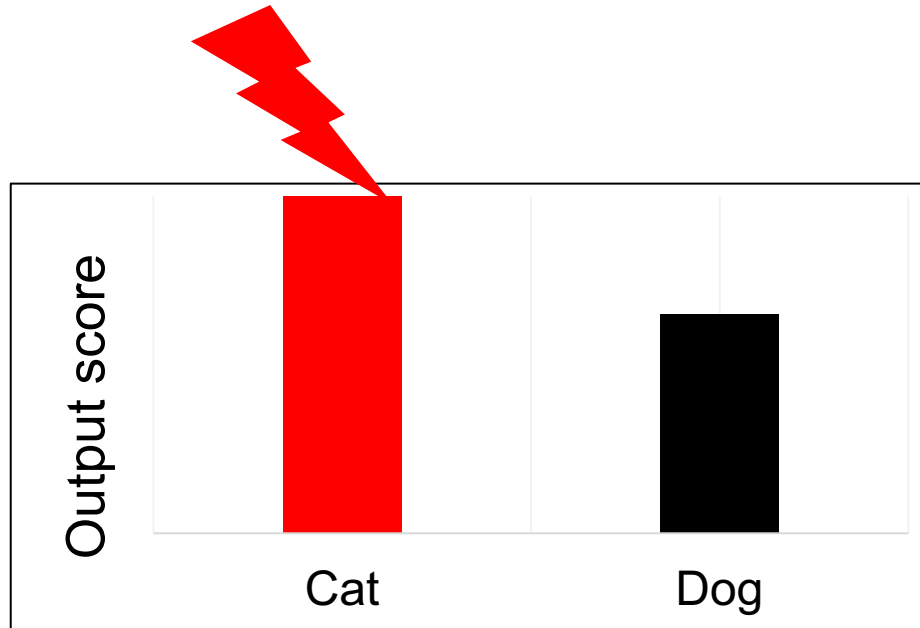


With **benign** fault  
Classify as ``dog``



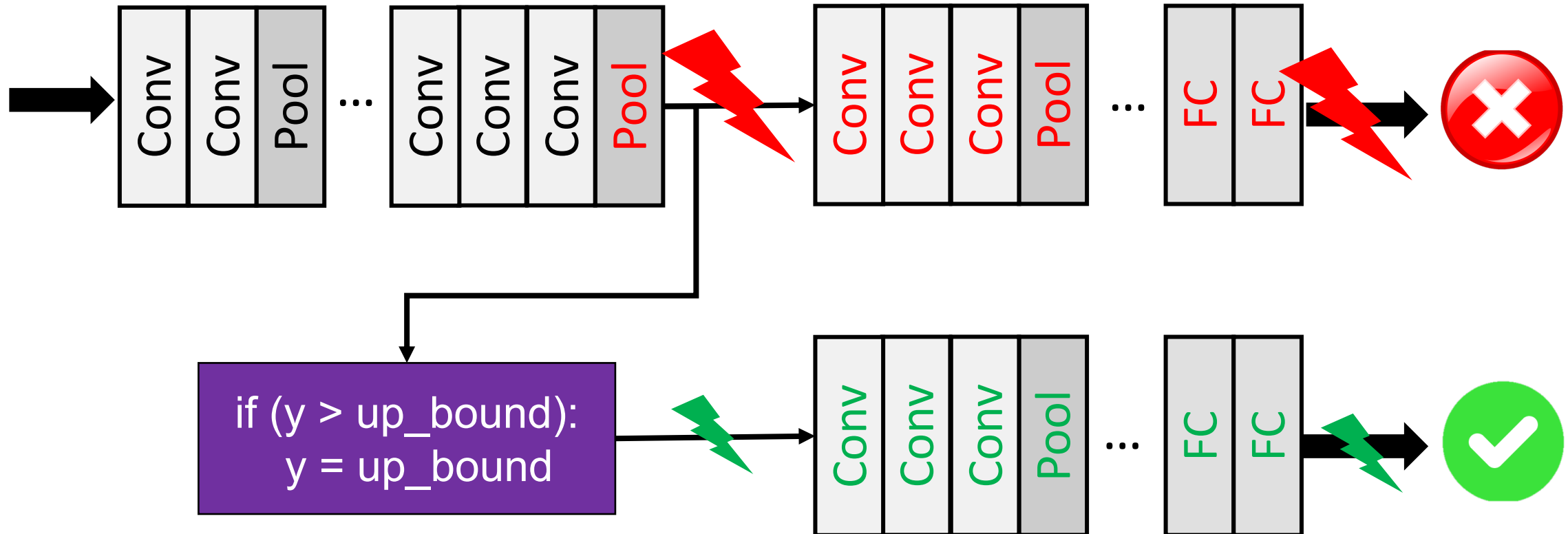
DNNs can also be **reliable**

# Our work



# Our solution: Ranger

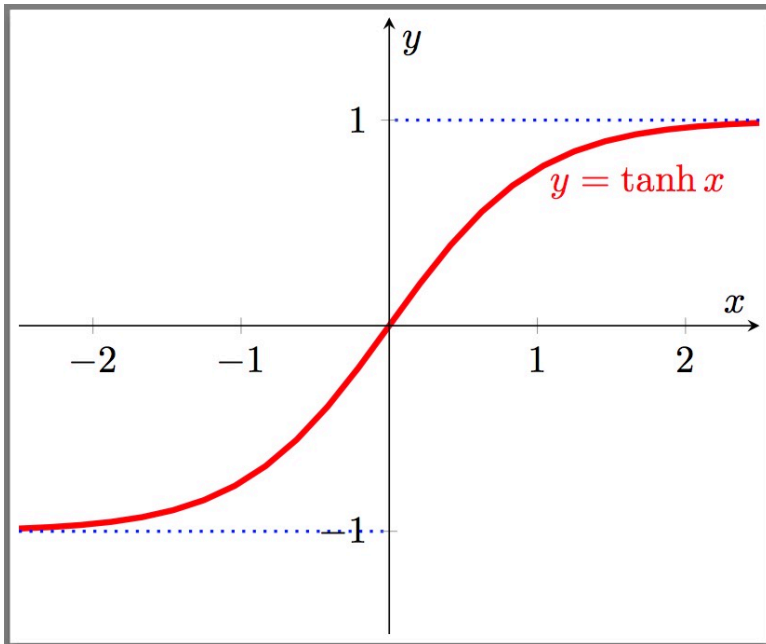
- Range restriction in selective layers



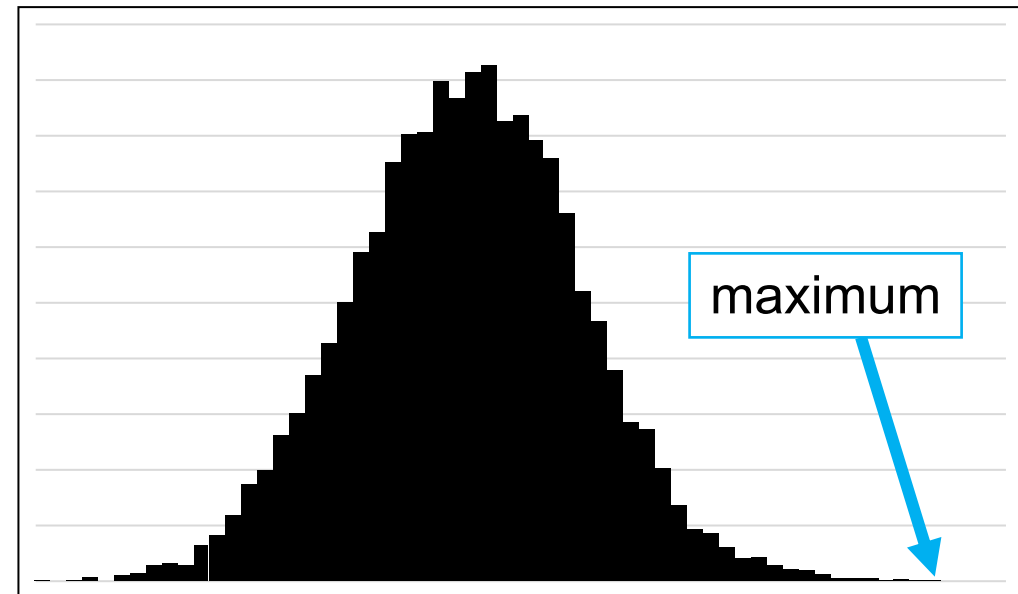


# How to derive restriction bounds?

Analytically



Statistically



# Where to perform range check?

Activation functions  
(e.g., Tanh, Relu)

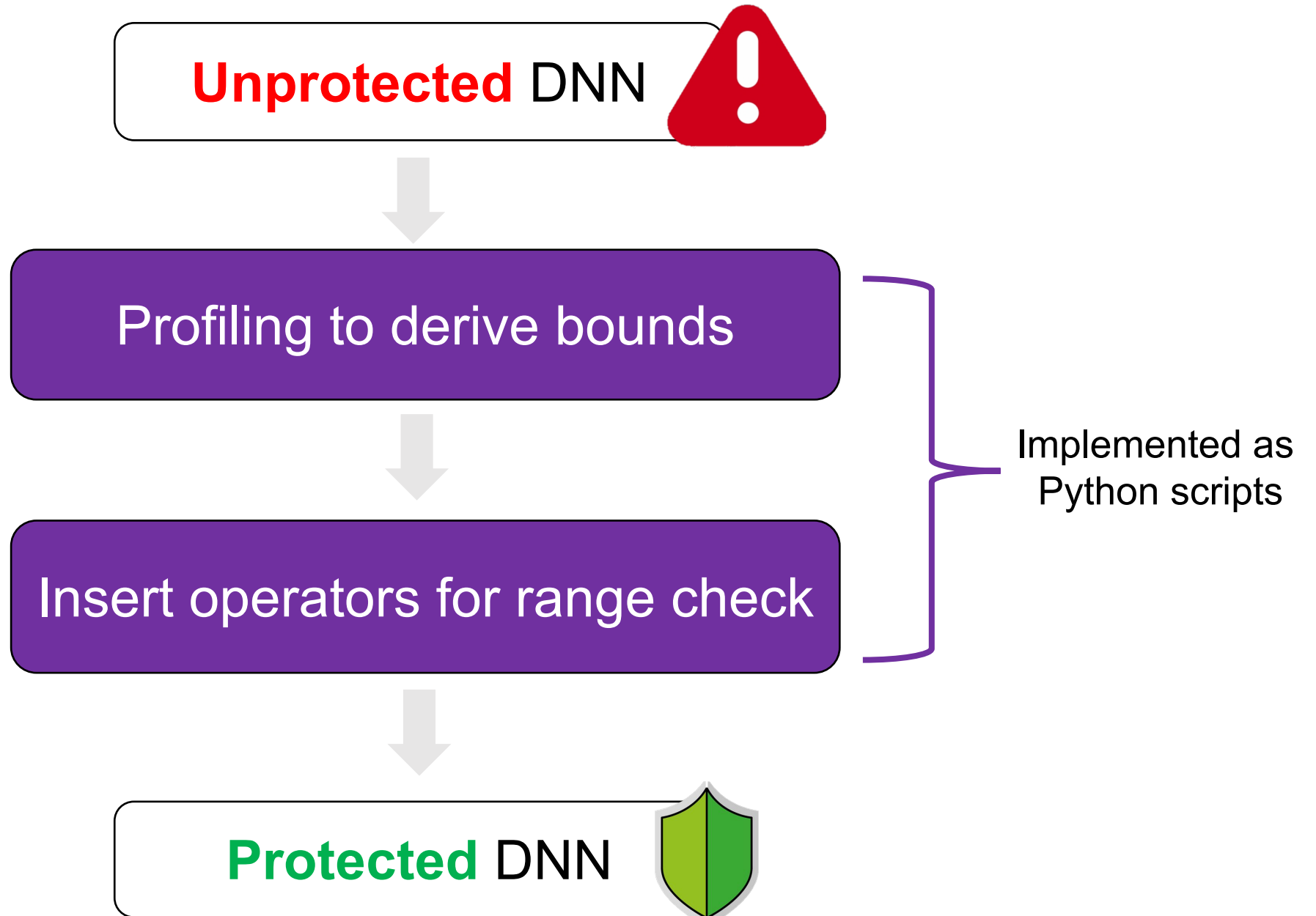
Pooling layers  
(e.g., MaxPool, AvgPool)

Reshape

Concat

- *Details in the paper*

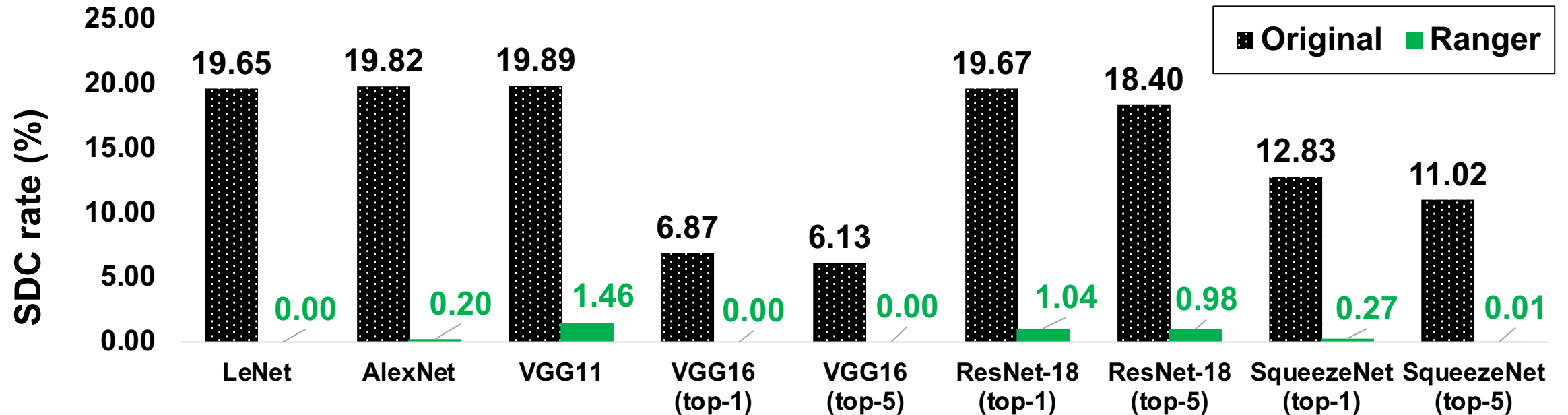
# Workflow



# Evaluation

<b>Model</b>	<b>Dataset</b>
LeNet	Mnist
AlexNet	Cifar-10
VGG11	German traffic sign
VGG16	ImageNet
SqueezeNet	ImageNet
ResNet-18	ImageNet
Nvidia Dave	Real-world driving scene
Comma.ai	Real-world driving scene

# Effectiveness of Ranger



SDC rate reduced from 14.92% to 0.44%  
(34X reduction)

# Accuracy of DNNs

No accuracy degradation for the DNNs  
(without fault)

# Overhead

0.53%  
Floating-point Operations (FLOPs)

# Ranger in action



Prediction (without fault):  
**156.58°**



Prediction (**with** fault):  
**-78.09°**



Prediction (**with** fault):  
**(with Ranger) 155.97°**

**Ranger corrects the faulty value to an acceptable value to navigate the AV safely !**

# Summary

## **DNN reliability is an important problem**

- Soft errors can lead to failure outputs – need mitigation

## **Ranger: Selective Range Restriction**

- Transform **critical** faults → **benign** faults
- **Significant** SDC rate reduction, **no** accuracy loss, negligible overheads
- Code at <https://github.com/DependableSystemsLab/Ranger>

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# Reference

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- G. Li et al., “Understanding error propagation in deep learning neural network (dnn) accelerators and applications,” in Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis. ACM, 2017.
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