Dependability Evaluation and Enhancing Methods for Transformer Models

ETS PHD FORUM

Transformers models

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  - Many tasks

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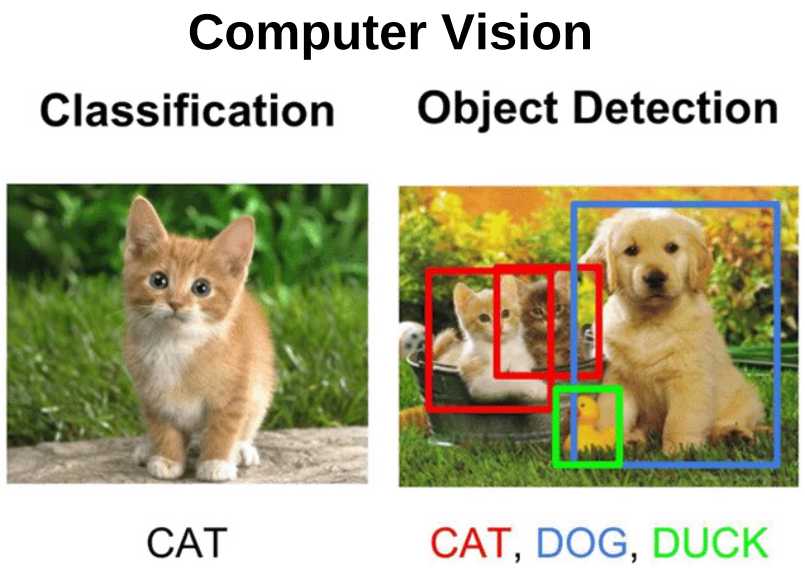

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Computer Vision **NLP**

Classification **Object Detection**

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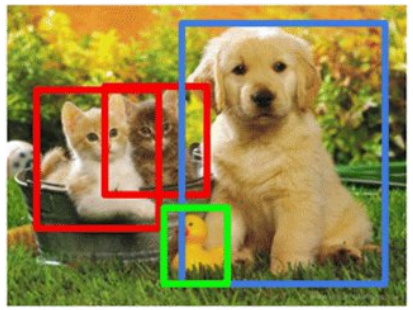

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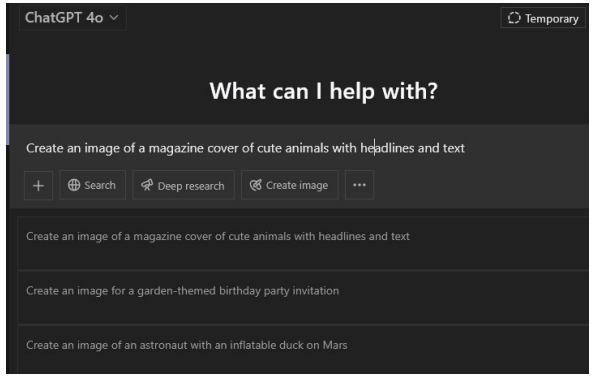

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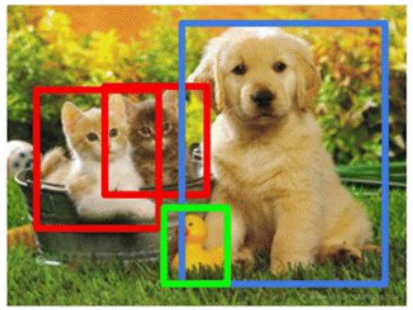

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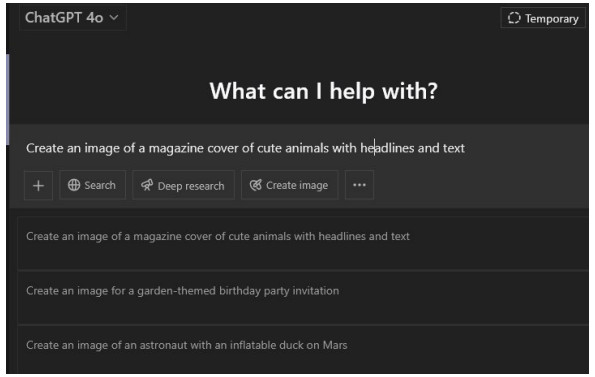
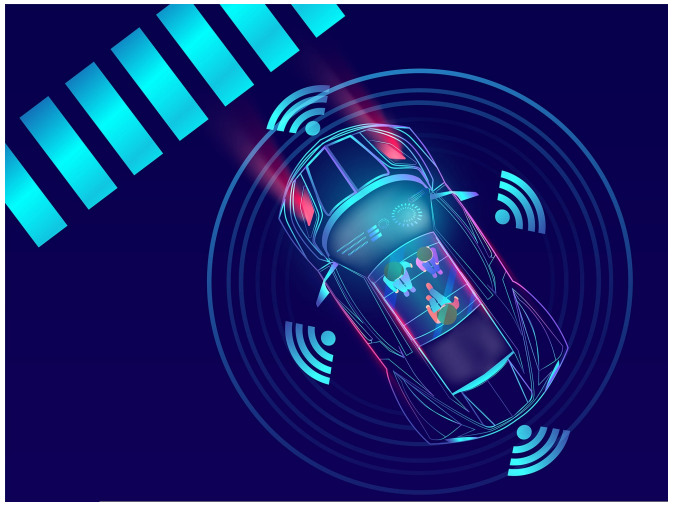


Safety-critical systems



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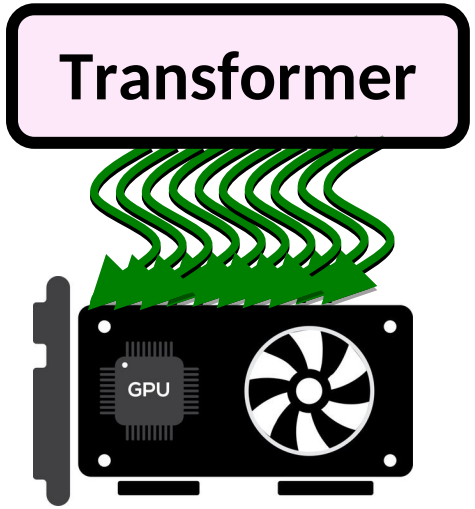

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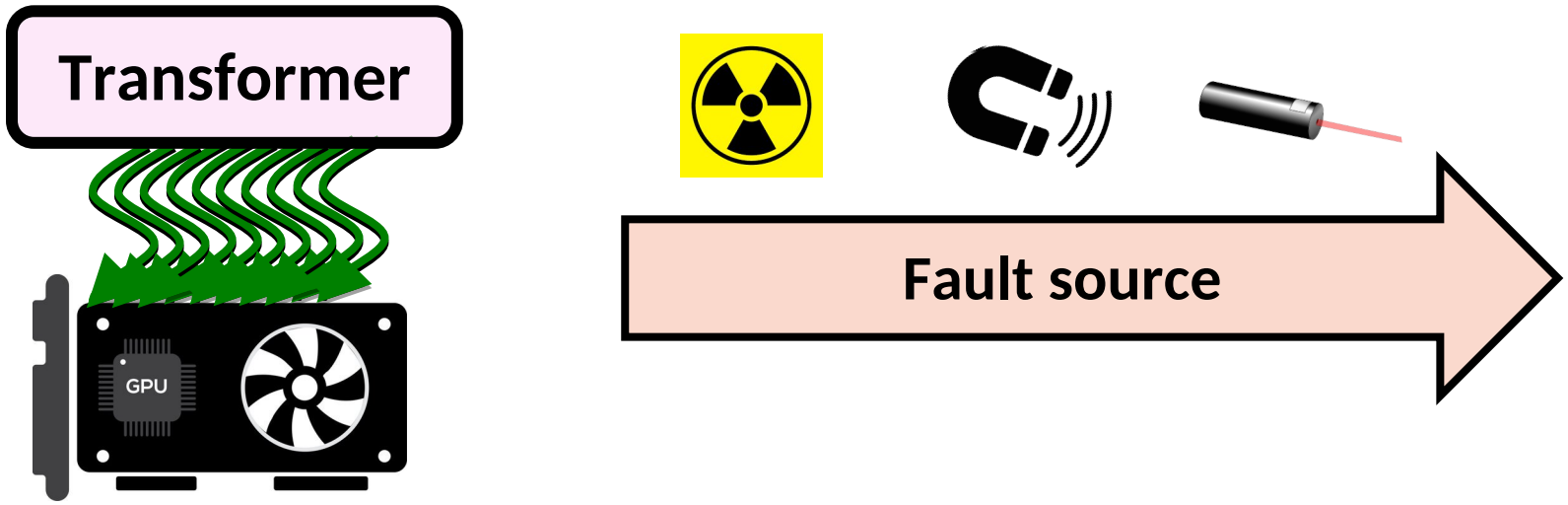

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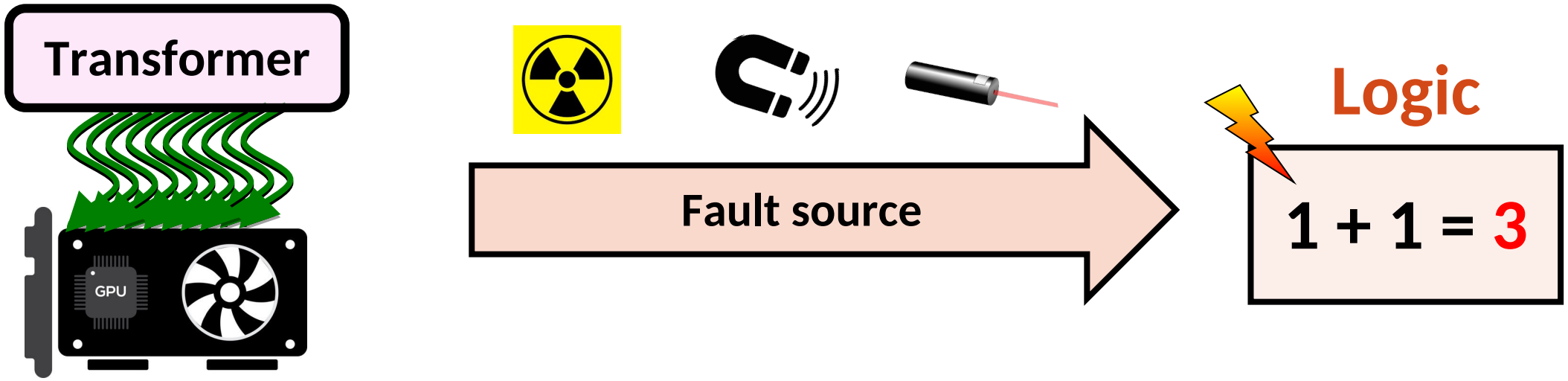

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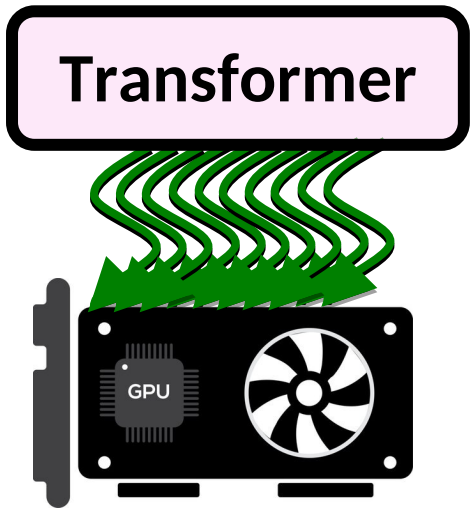

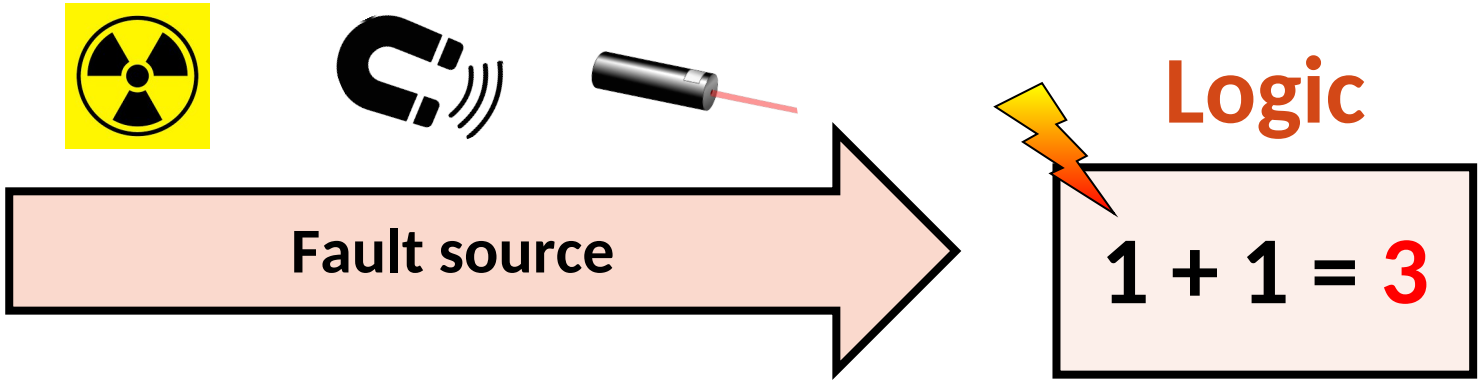

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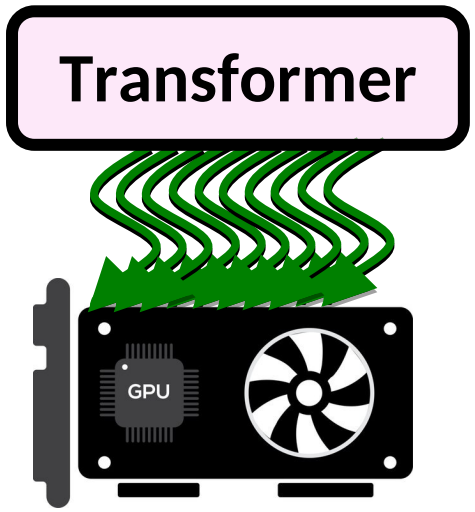

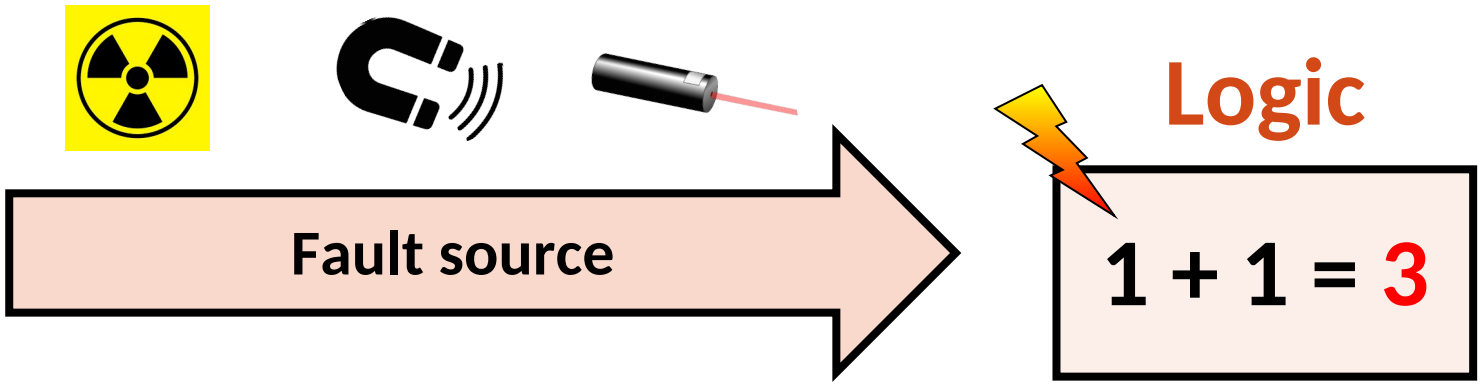

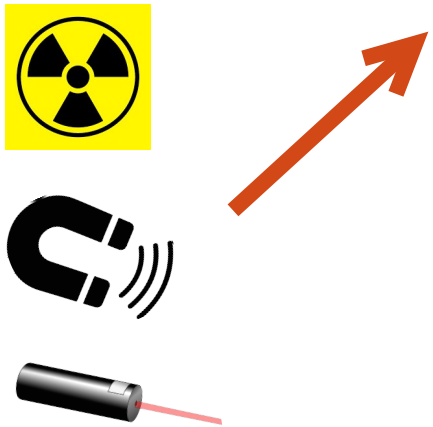

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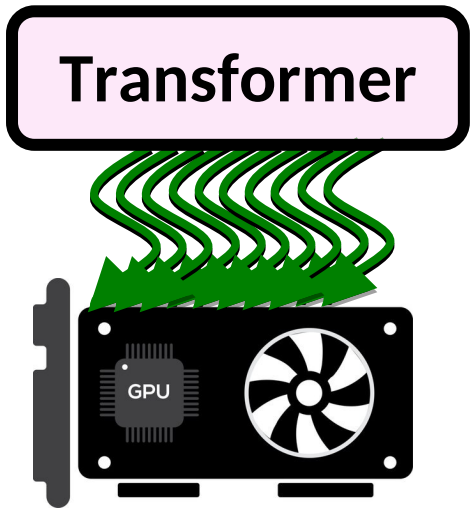

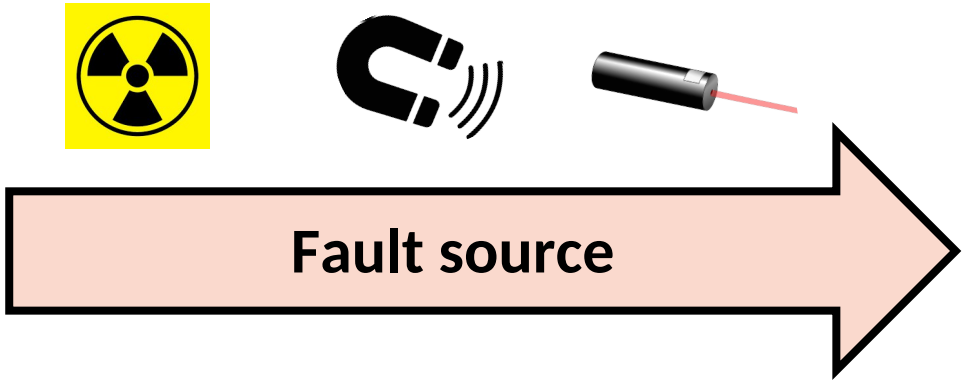

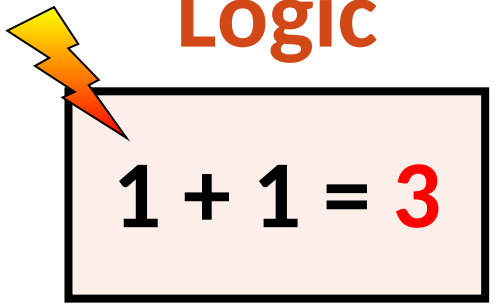

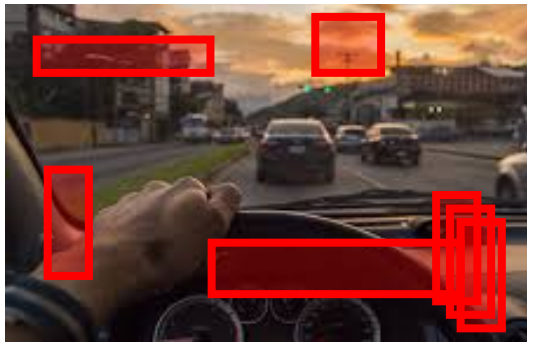

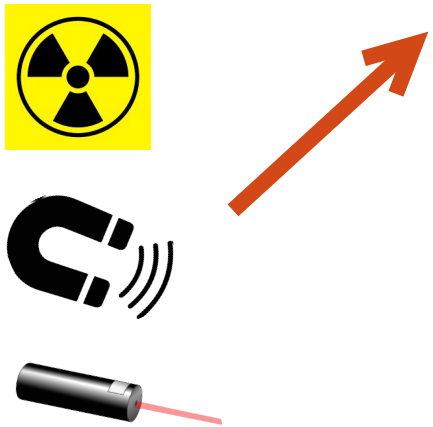

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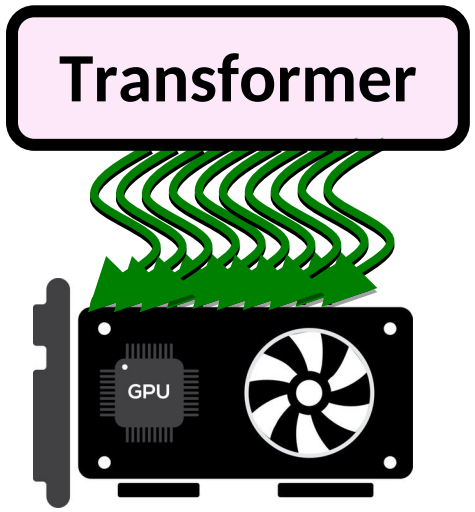

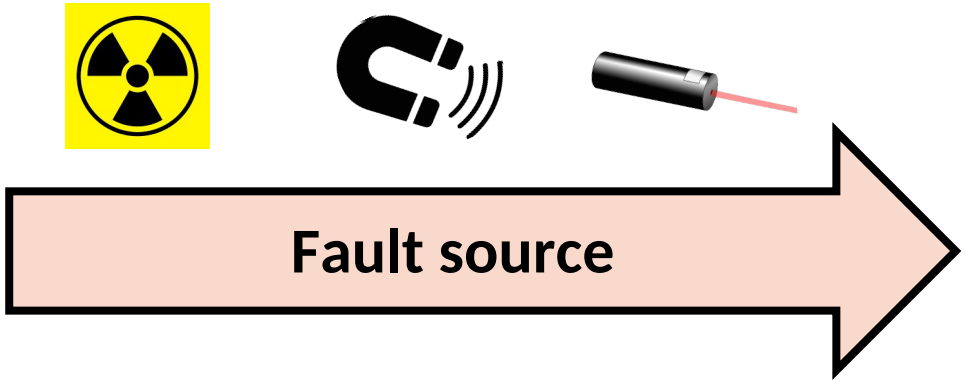

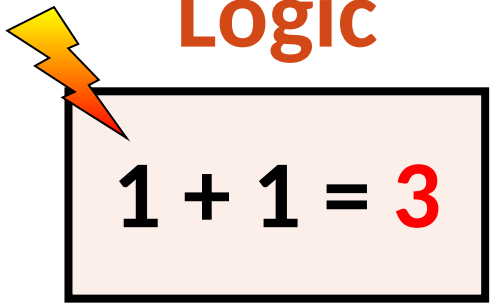

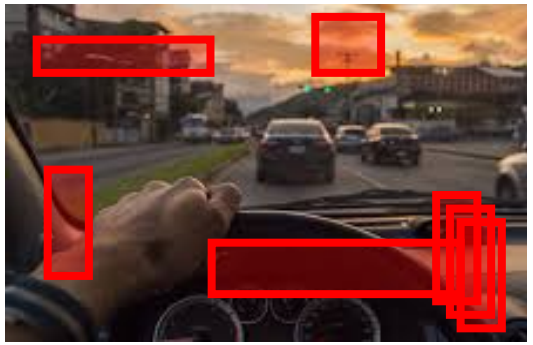

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Detected Unrecoverable Error (DUE)

- Crash and OS hangs

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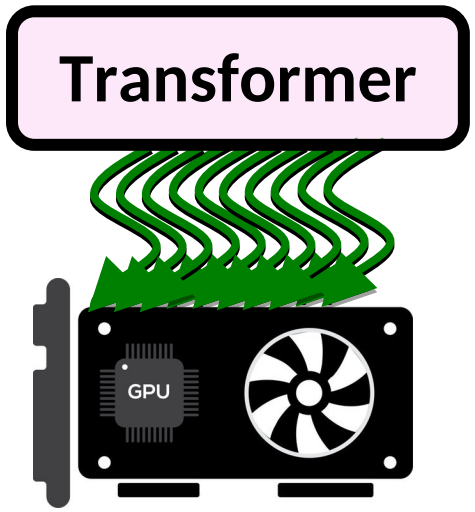

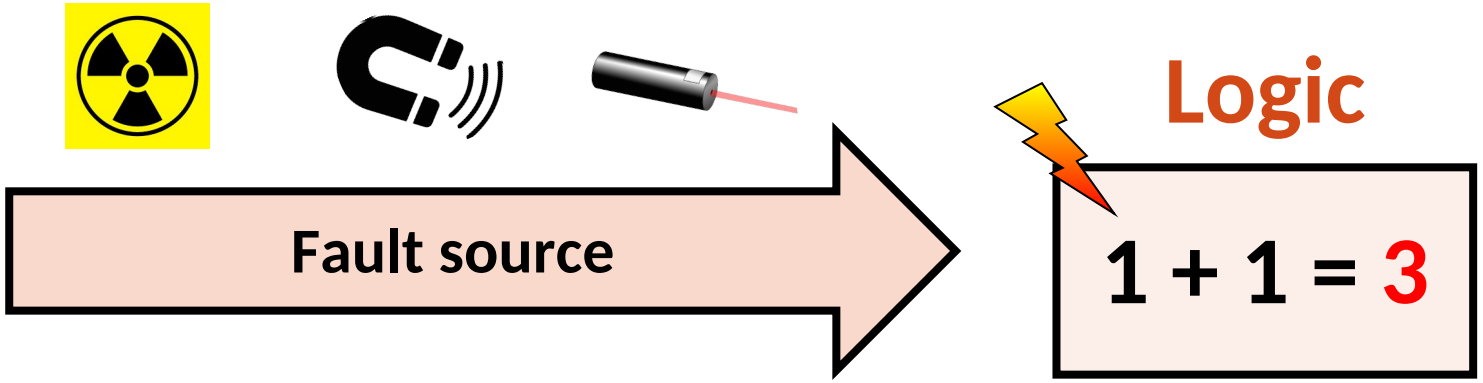

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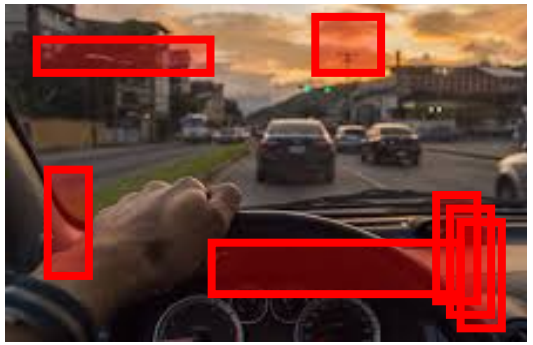

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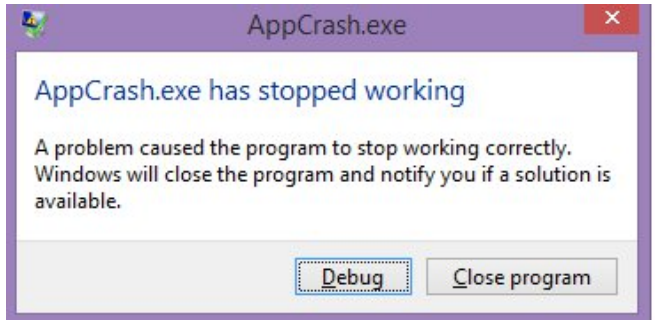

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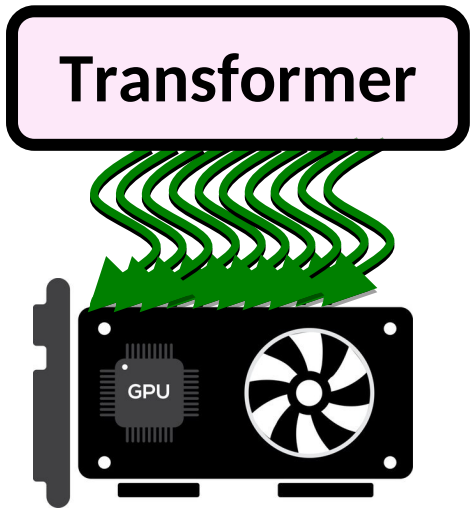
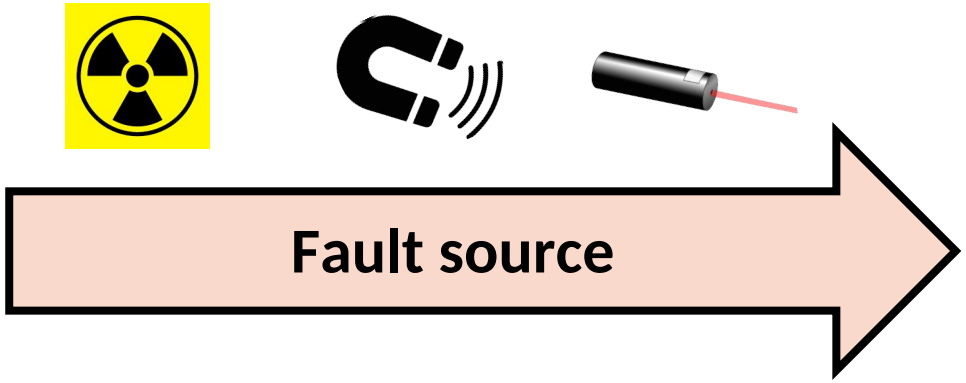
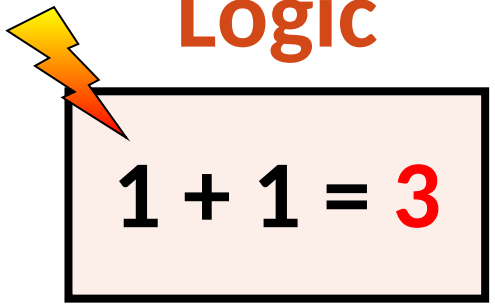
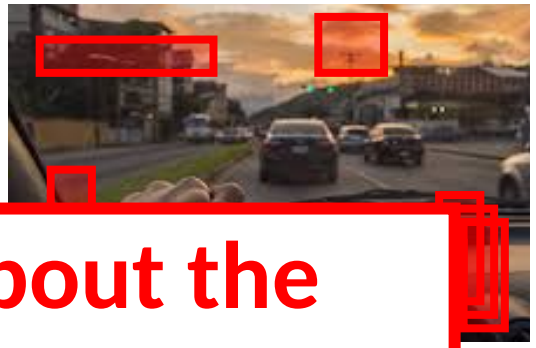




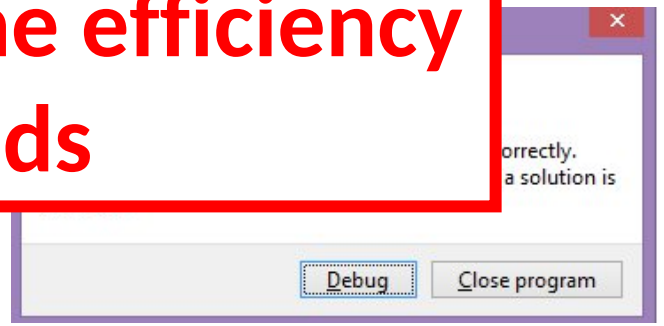




Silent Data Corruption (SDC)

This raises multiple questions about the assessement methodology and the efficiency of the protection methods

- Crash and OS hangs



One under-explored variable: inputs

For a dataset of N classes

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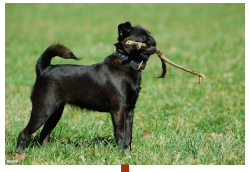

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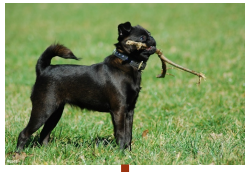

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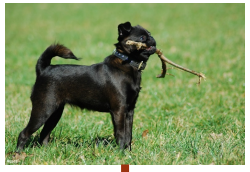

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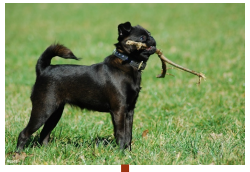

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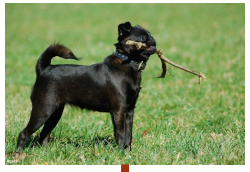

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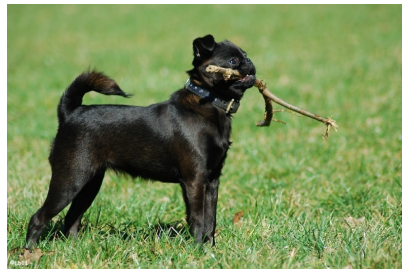

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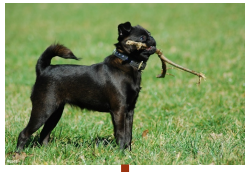

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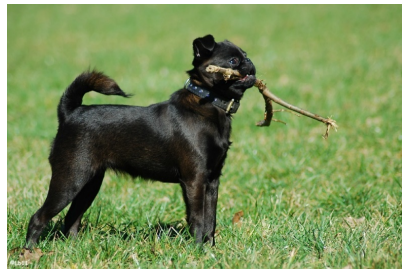

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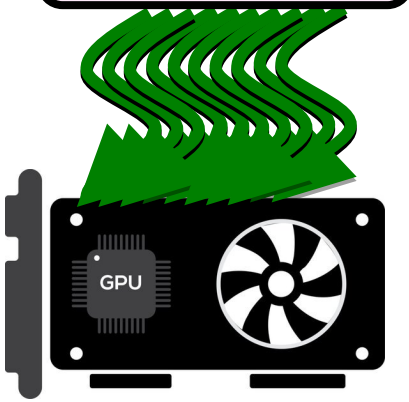

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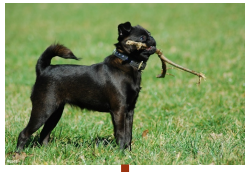

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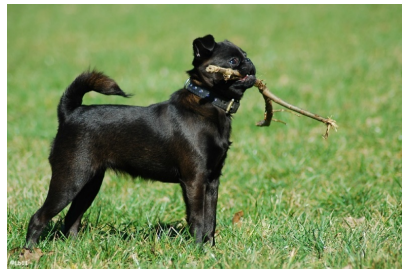

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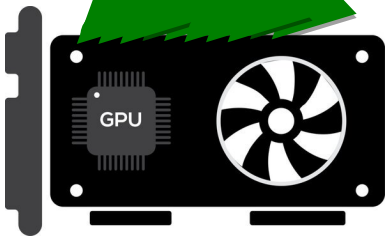
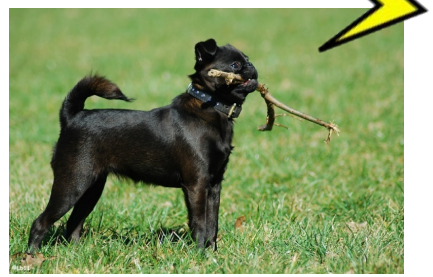


Less critical?



Conf.: 80%, Class: Dog

More critical?

Conf.: 5%, Class: Dog

Results in a nutshell

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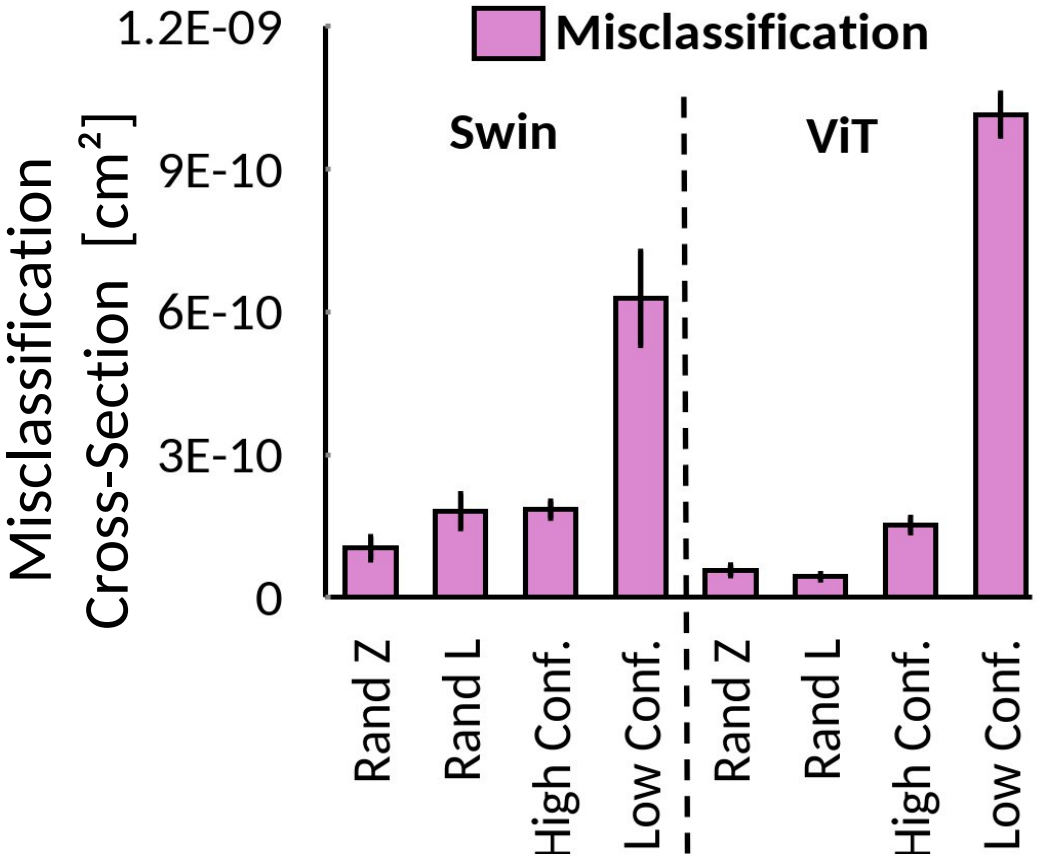
Neutron beam (unprotected) [1]*



[1] L. Roquet, IEEE TNS, 2026

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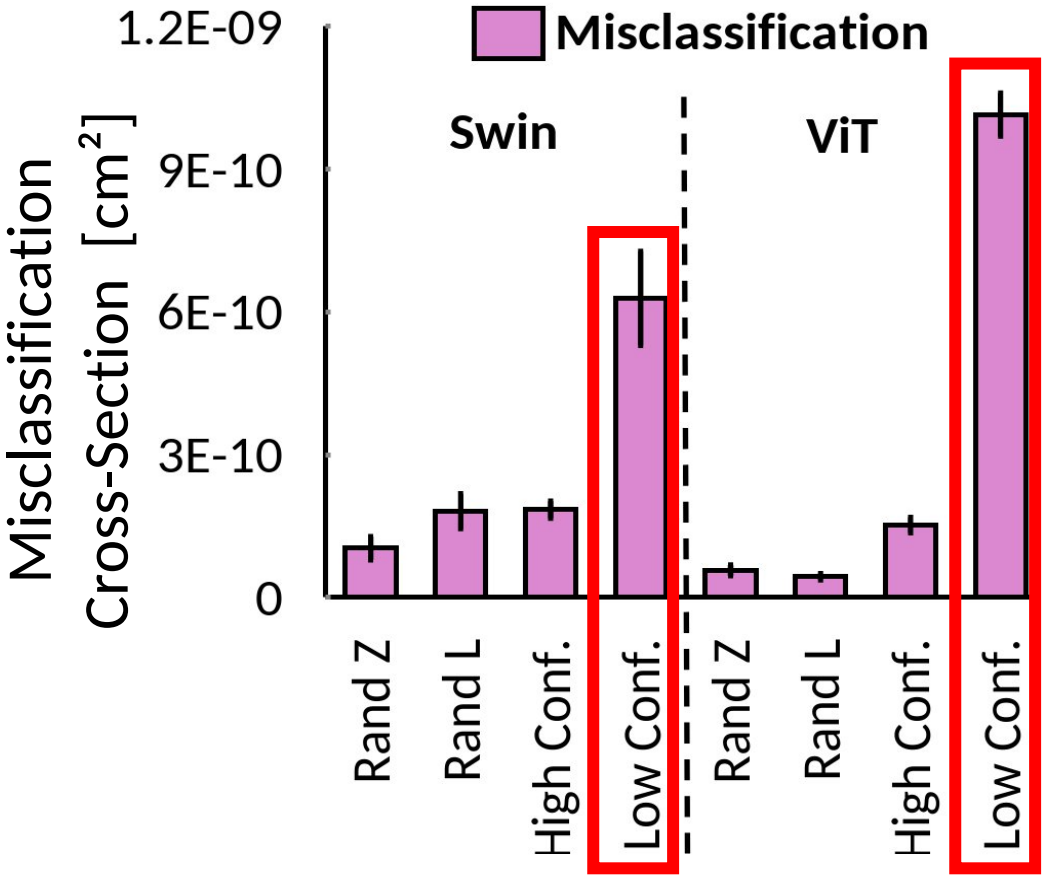

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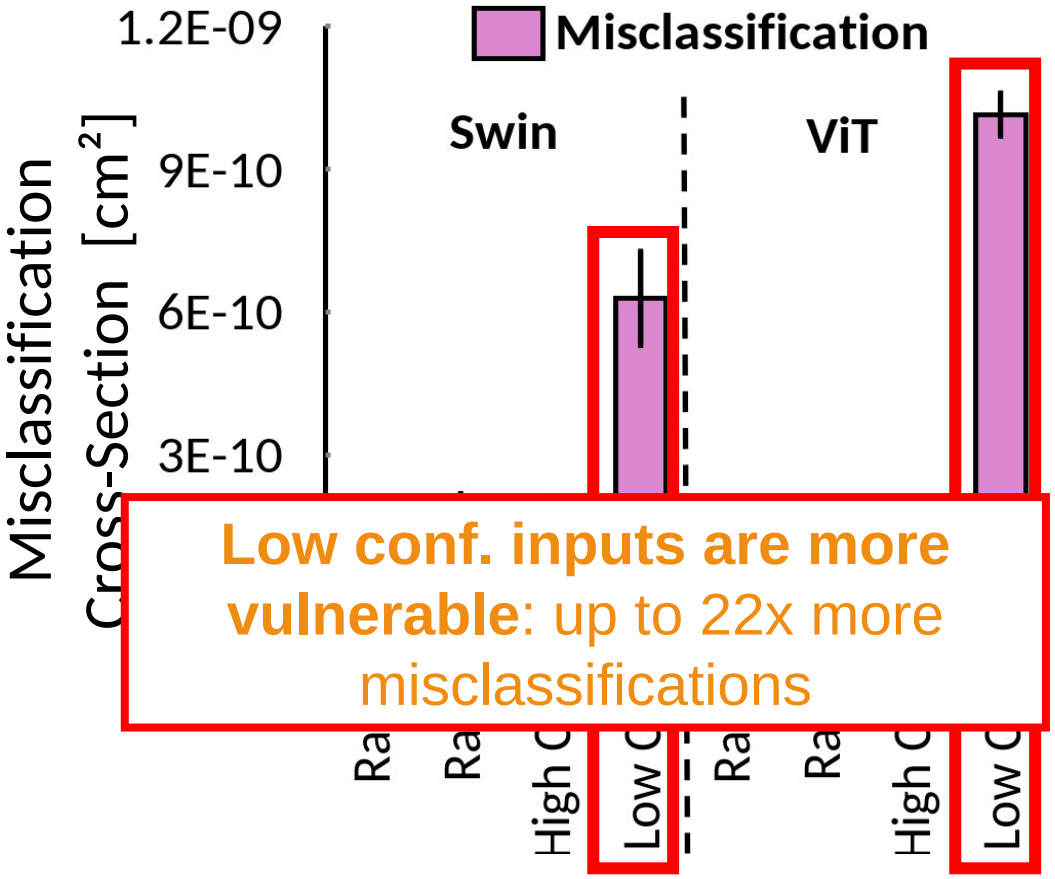

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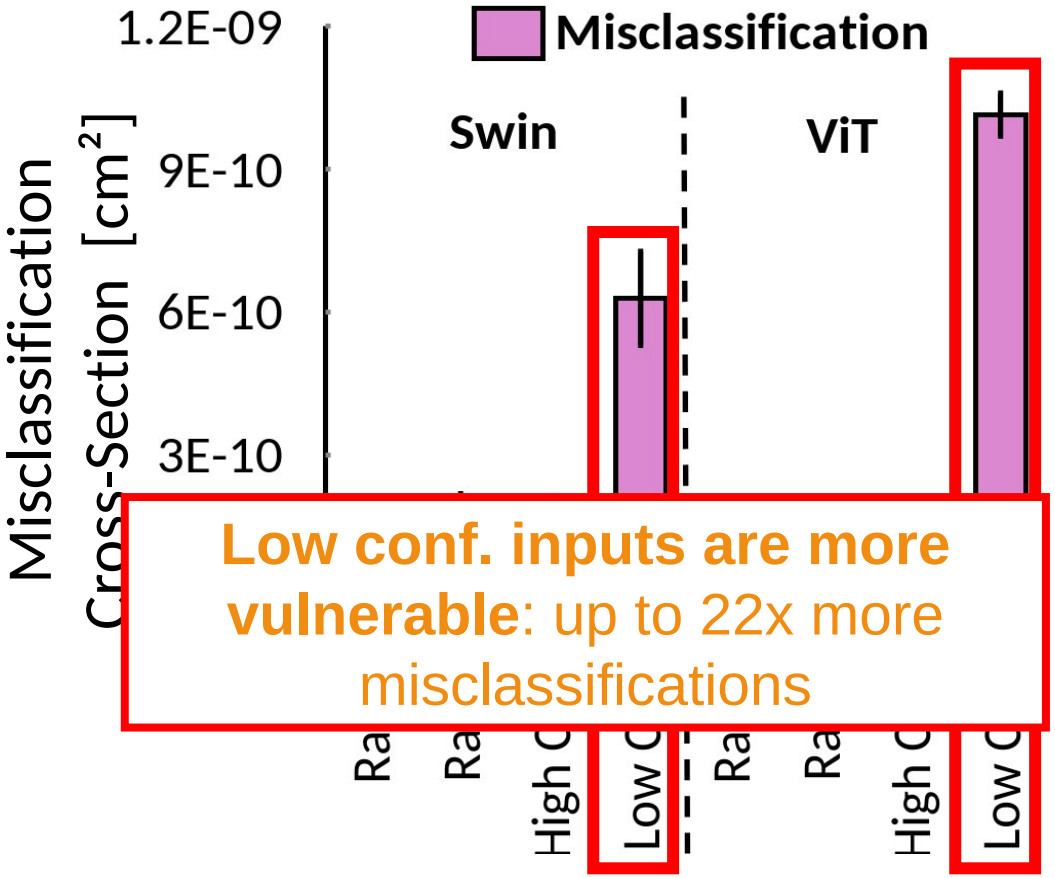

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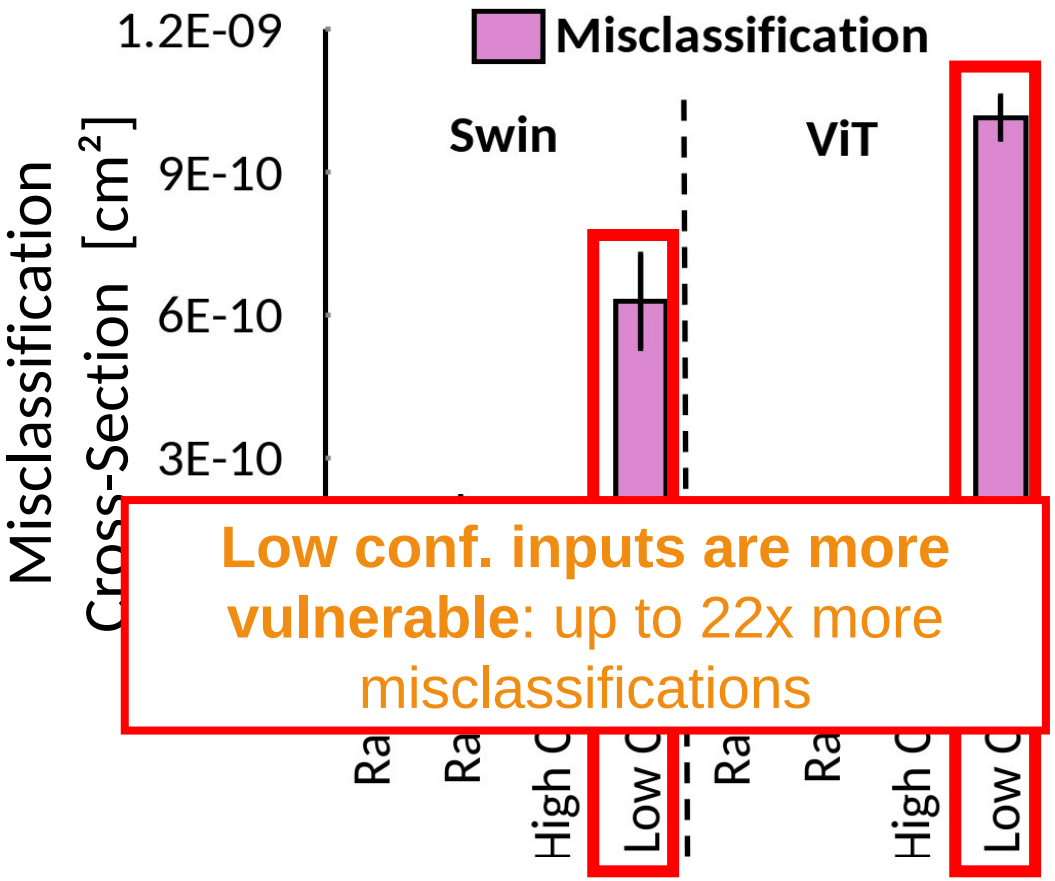

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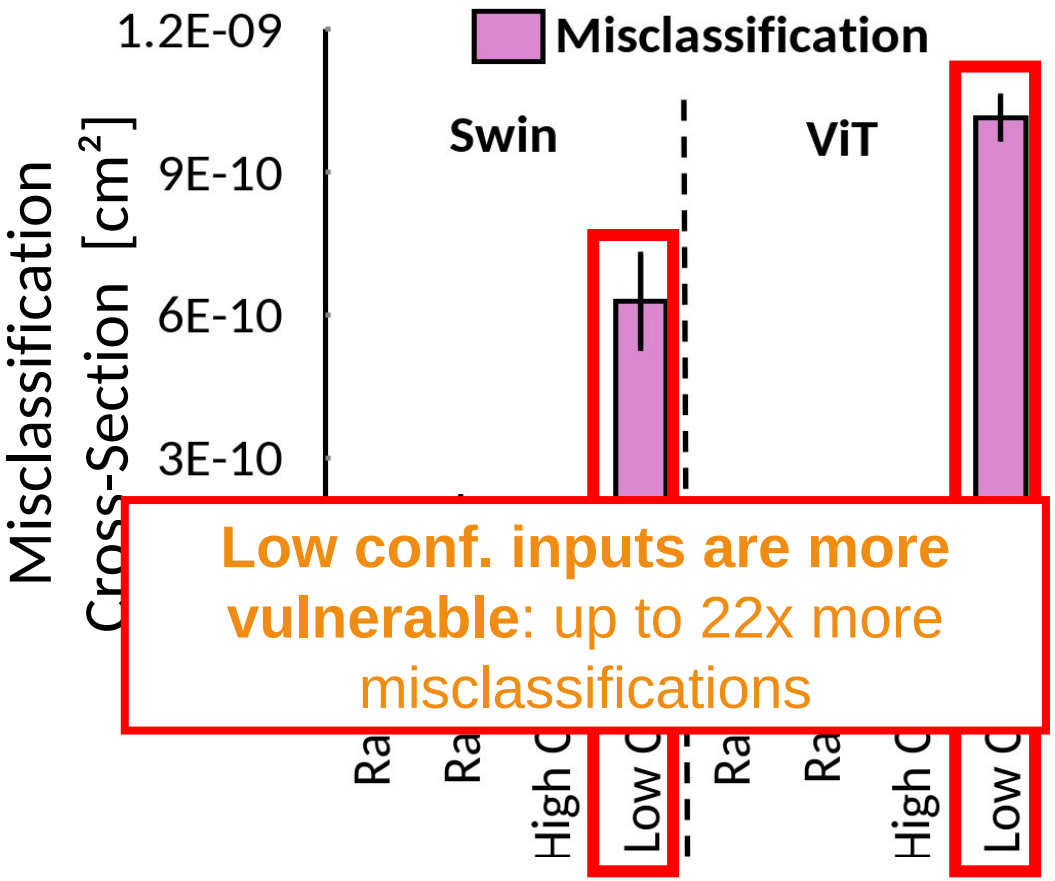
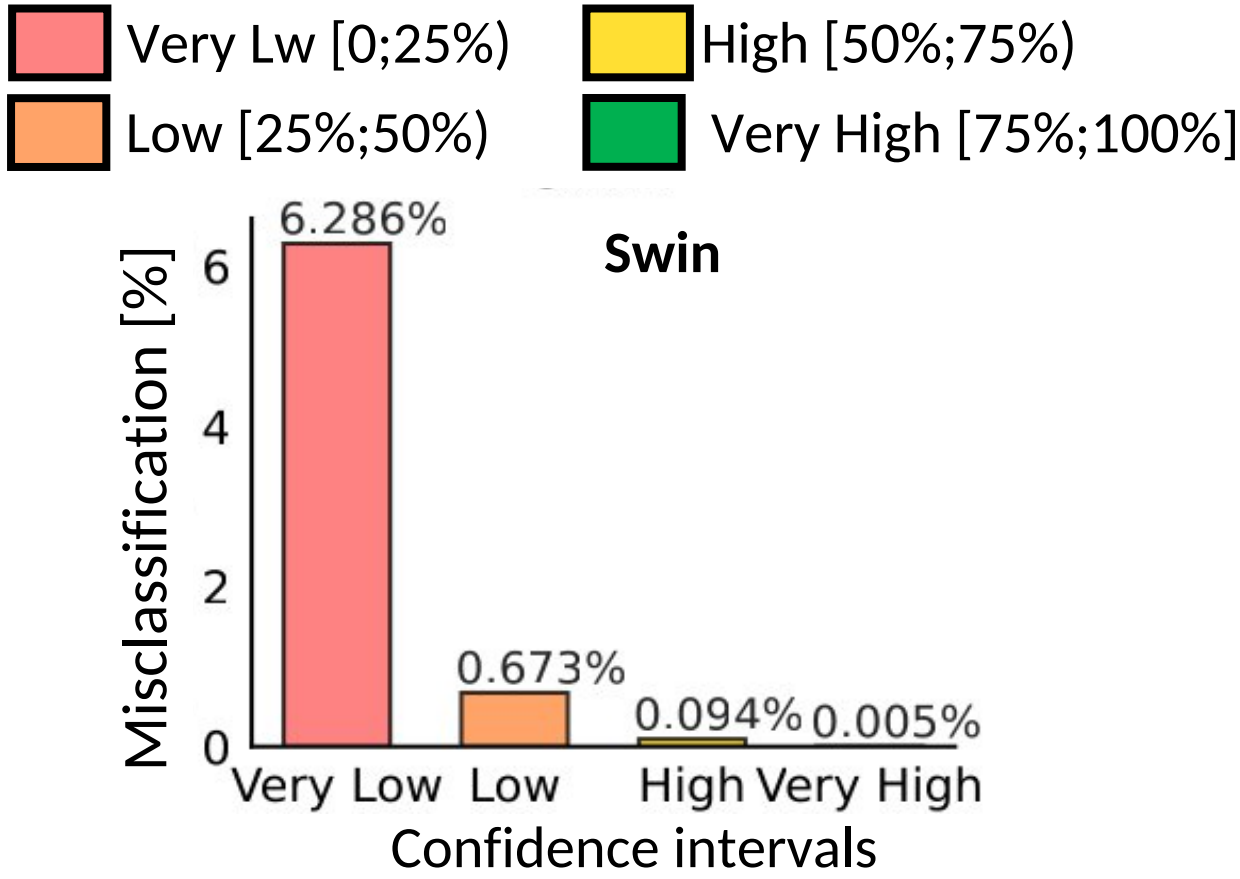
Neutron beam (unprotected) [1]*



Low conf. inputs are more vulnerable: up to 22x more misclassifications

*Same trends are observed by injecting fault at software level

Fault simulation (protected) [2]†



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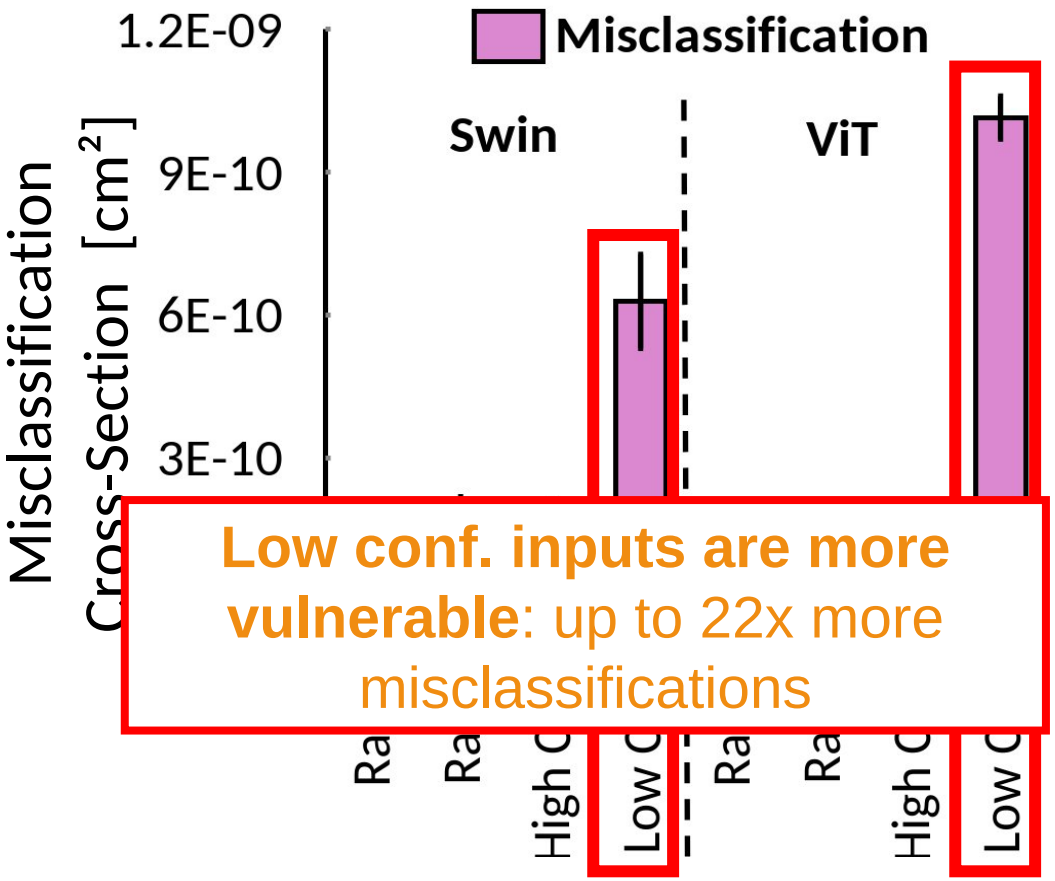

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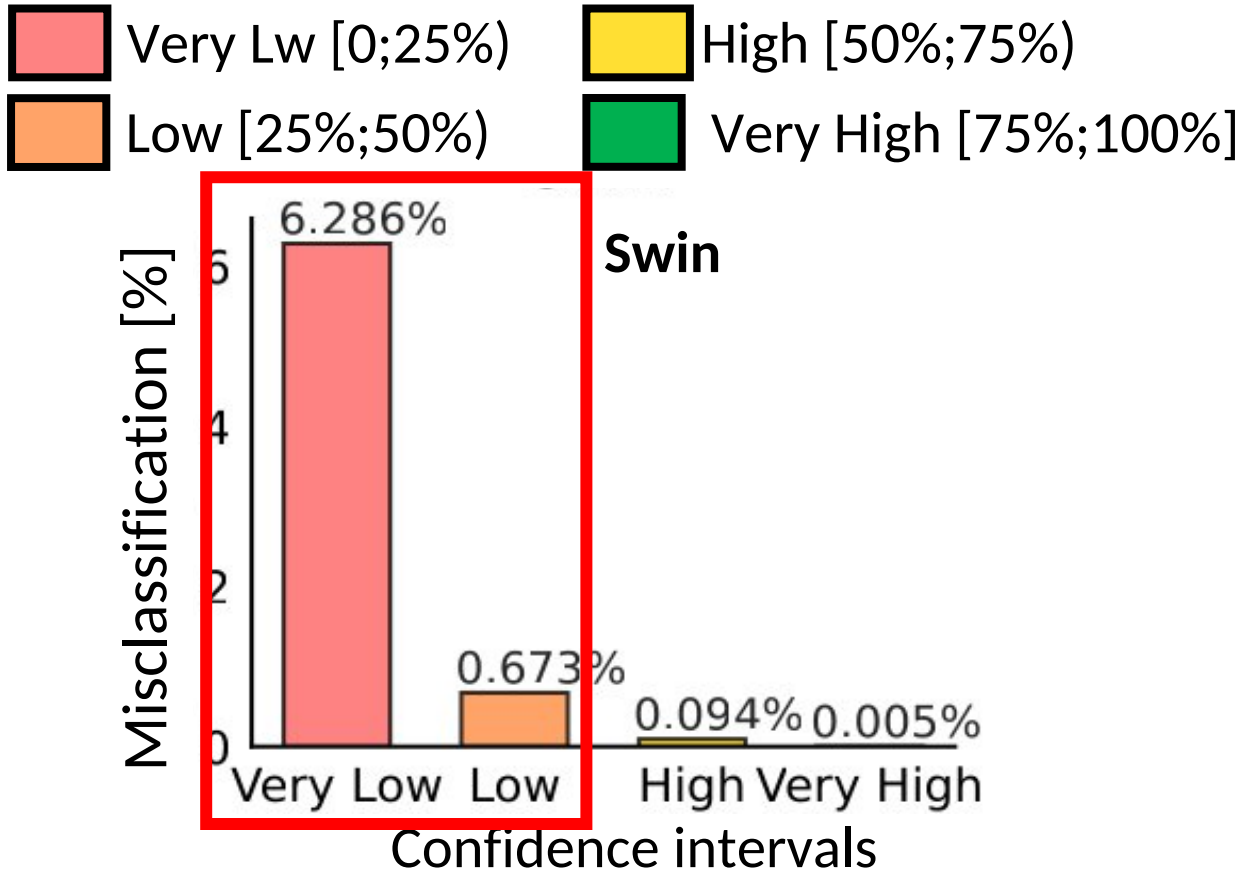

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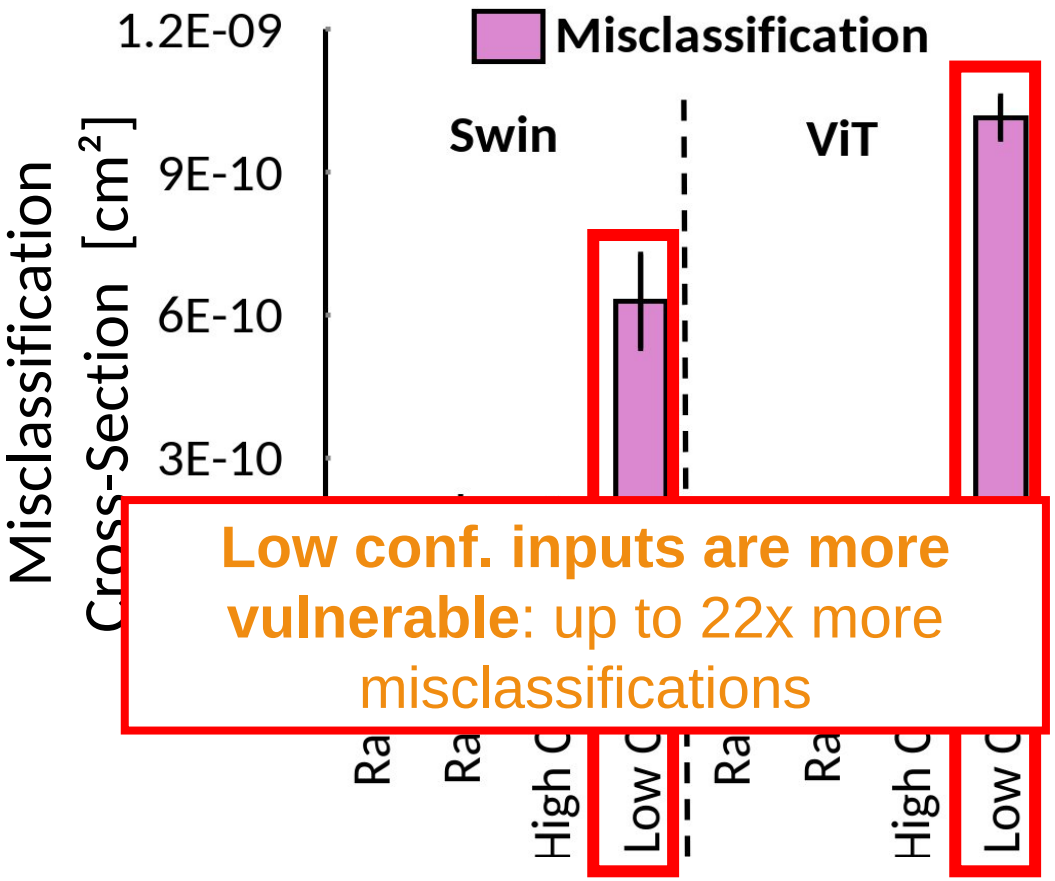

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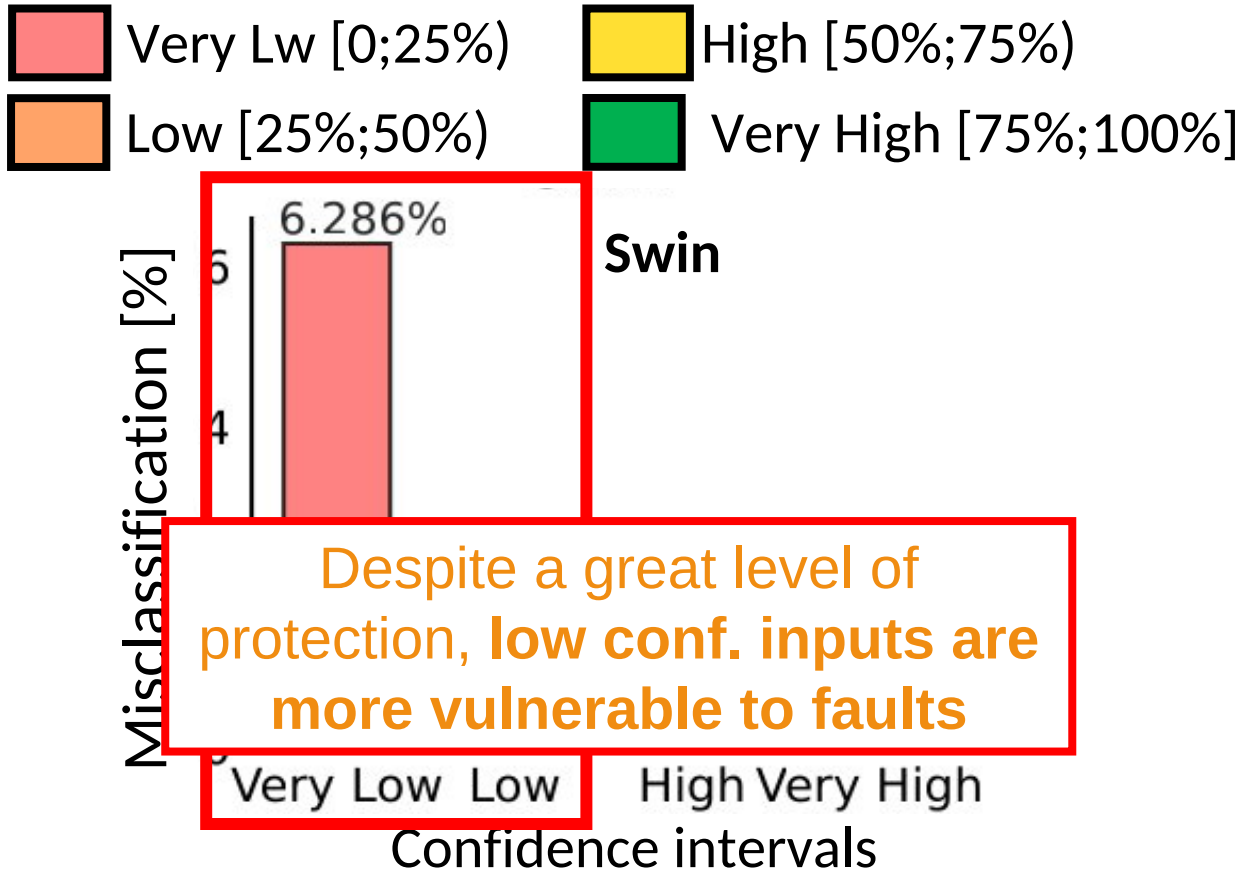

Despite a great level of protection, **low conf. inputs are more vulnerable to faults**

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Results in a nutshell

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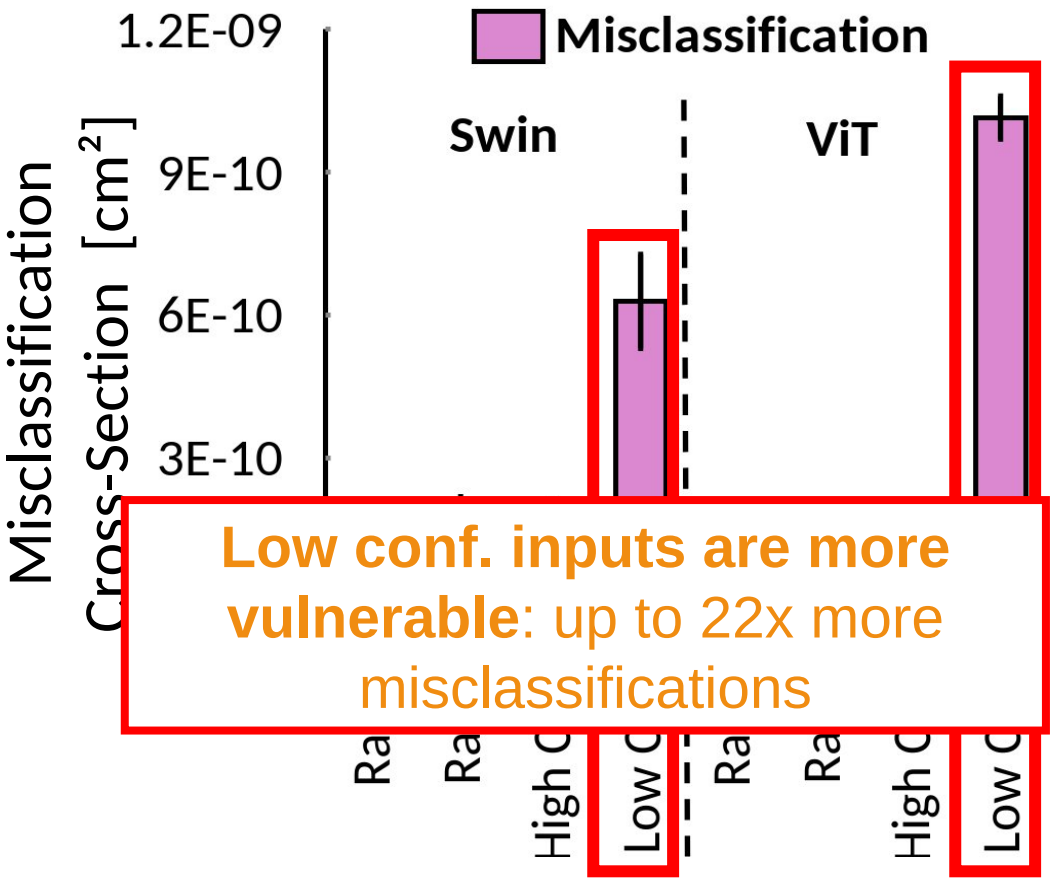

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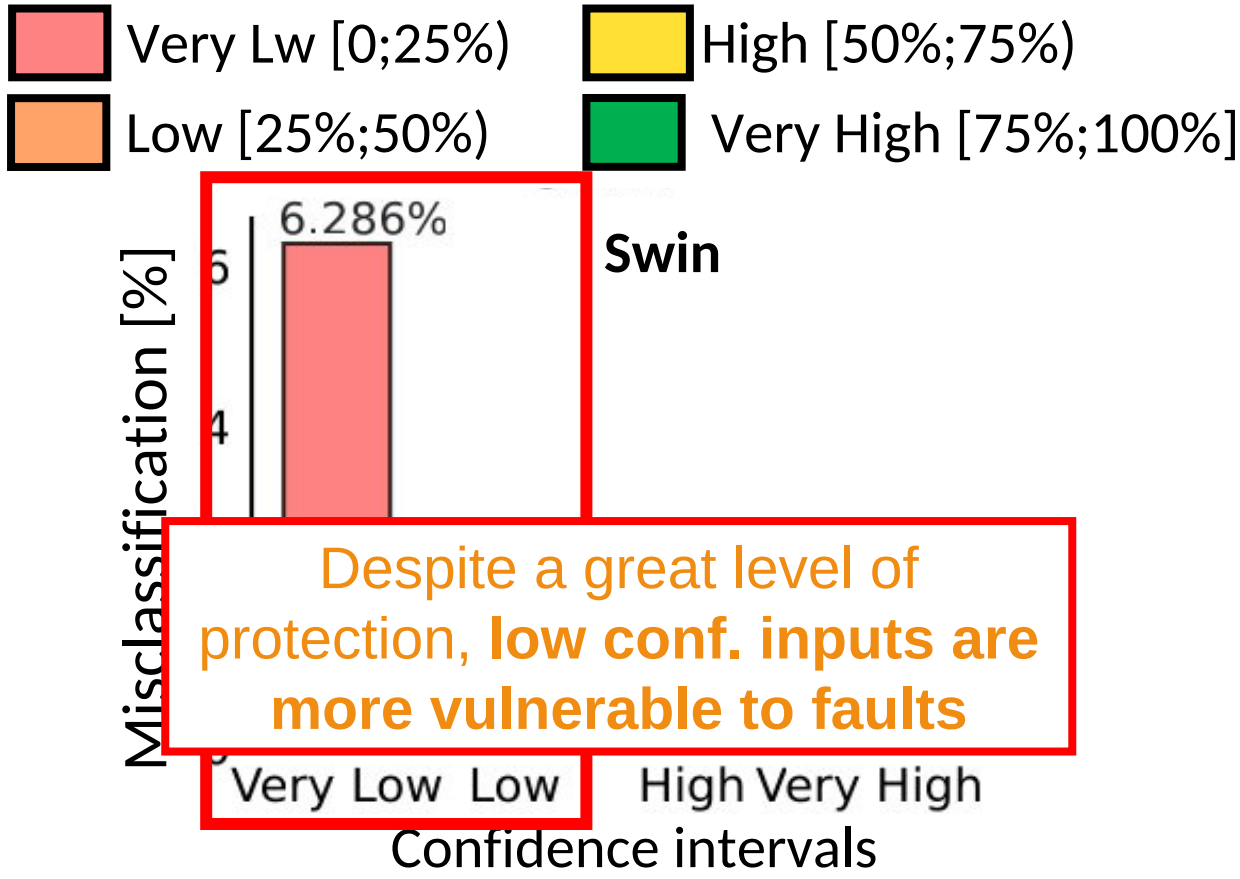

Despite a great level of protection, **low conf. inputs are more vulnerable to faults**

†Same trends are observed on 4 different models (CV & NLP)

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Thank you

Don’t hesitate to come see my poster

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