The Unlikely Hero: Nonideality in Analog Photonic Neural Networks as Built-in Defender Against Adversarial Attacks

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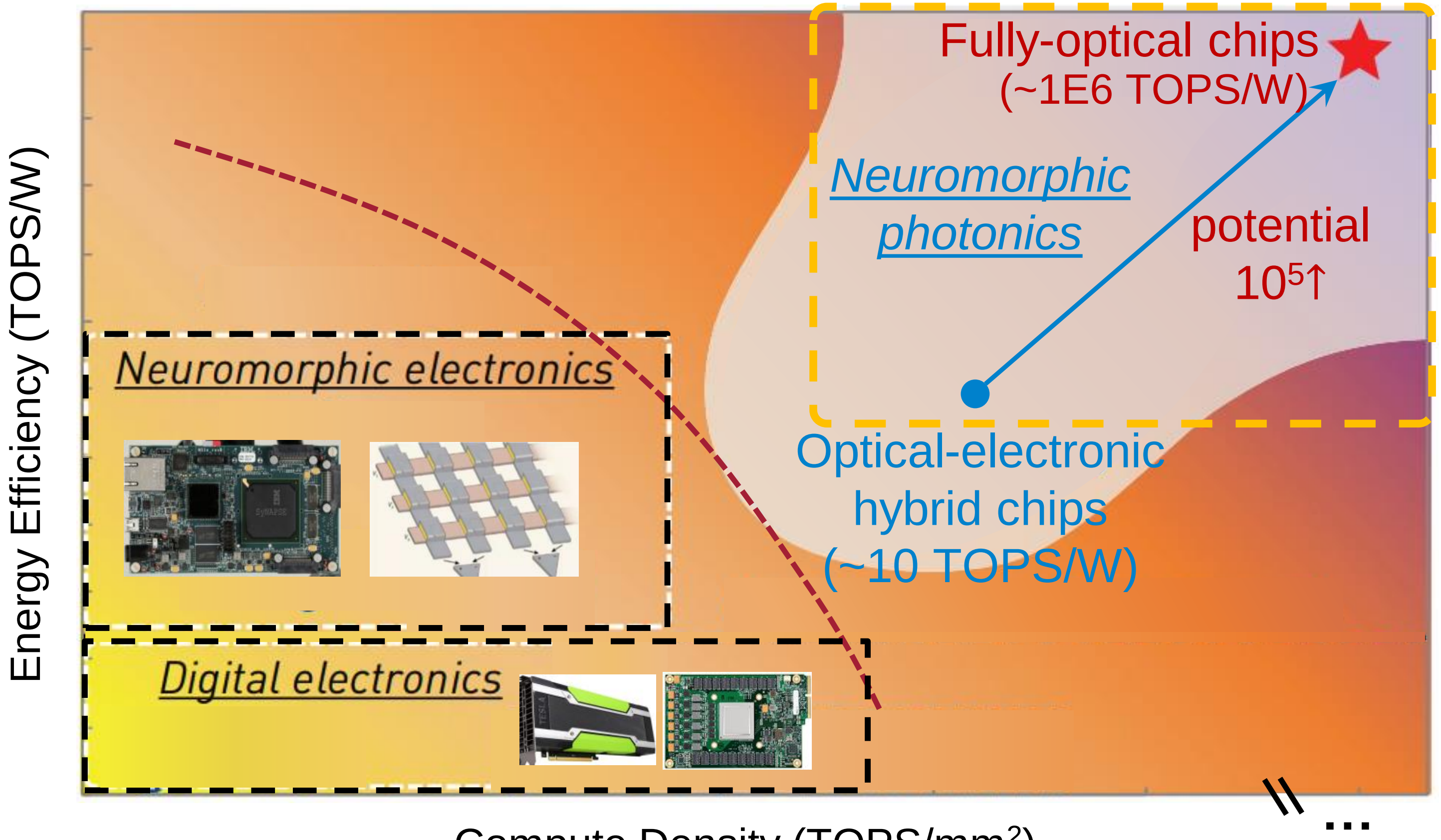
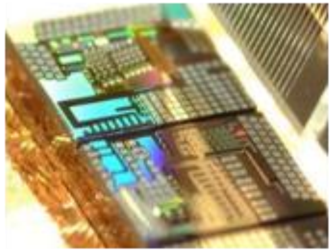
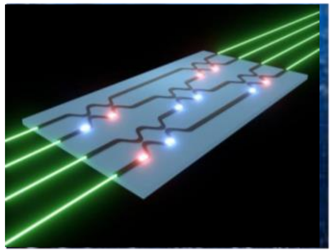
Photonic ML Accelerators

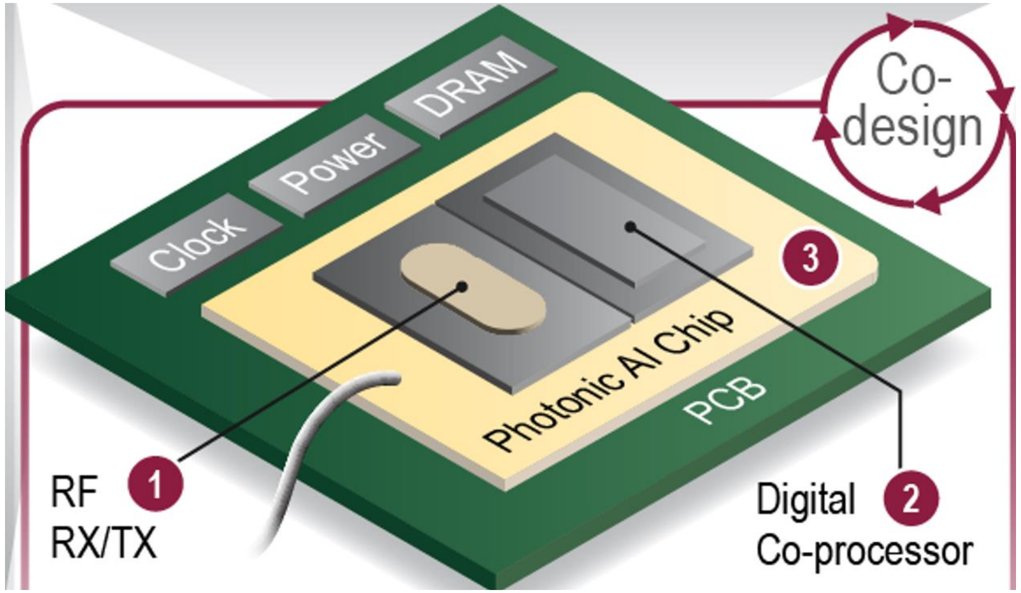
- Evolve from electronics to *heterogenous electronics-photonics*

Speed-of-light, Massive parallelism, low-power





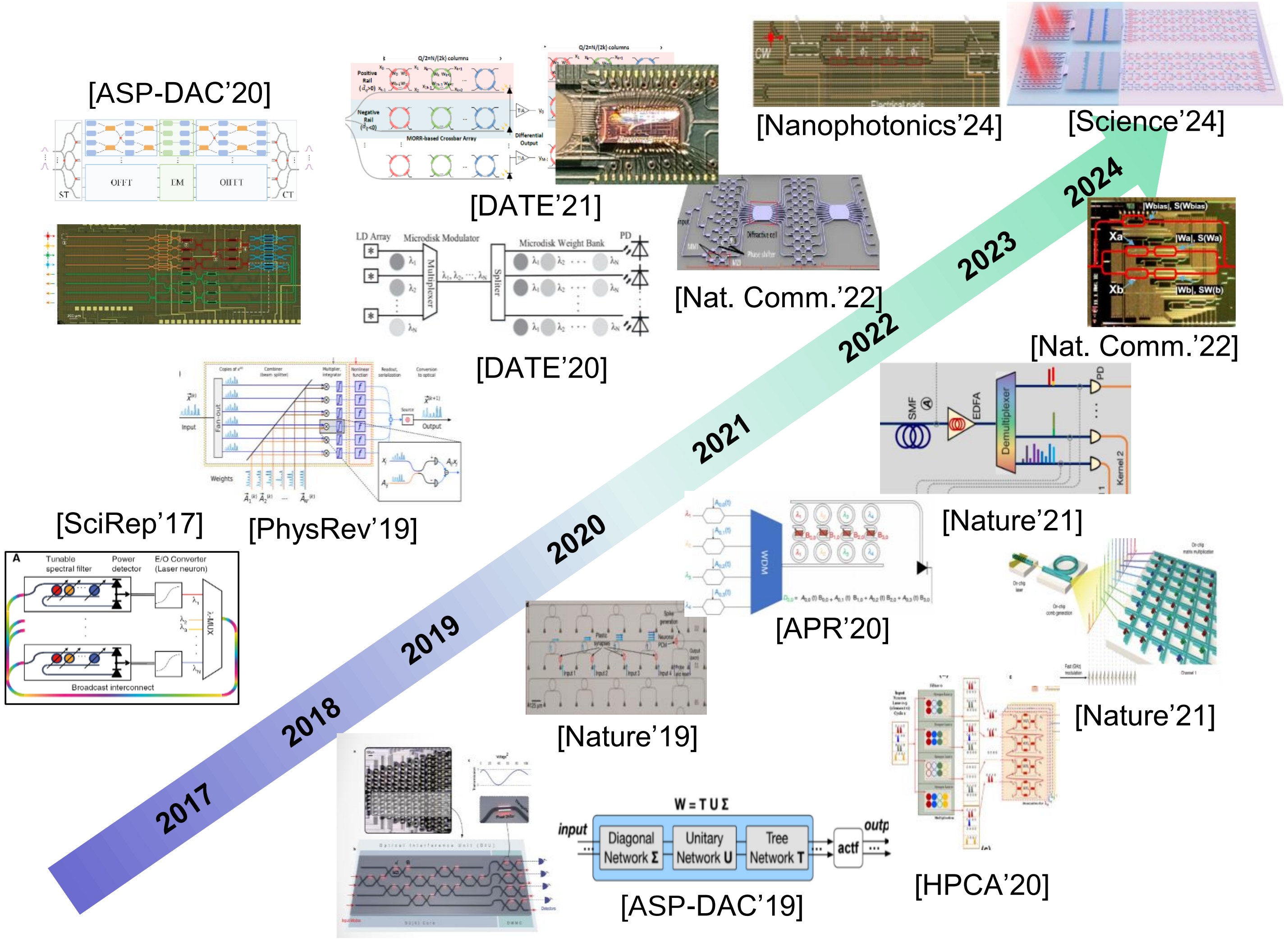




Source: Mitchell A. Nahmias, Bhavin J. Shastri, Alexander N. Tait, Thomas Ferreira de Lima and Paul R. Prucnal, "Neuromorphic photonics," Optics & Photonics News, Jan 2018.

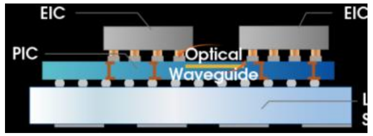
Photonic AI System is Booming

Photonic Neural Network Trends in Academia



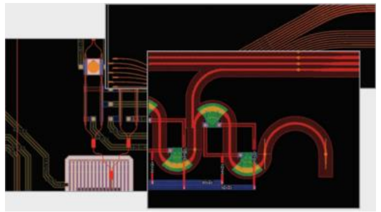
Foundry / EPDA Support in Industry

Photonic **Computing** Chip + Optical **Interconnects**



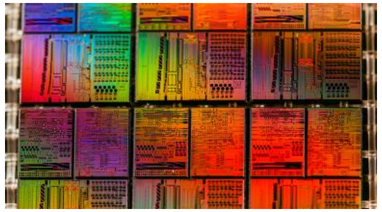
LIGHTMATTER
Lighton
XANADU
LIGHTELLIGENCE
OPTELLIGENCE
iPRONICS Programmable Photonics
OPTIUS light powered computing
SALIENCE LABS

Electronic-Photonic Design Automation Tools



Ansys LUMERICAL
SYNOPSYS PHOTONIC SOLUTIONS
cadence PHOTONICS
LUCEDA

PDK / Tape-out / HI / E-O Co-Packaging Support



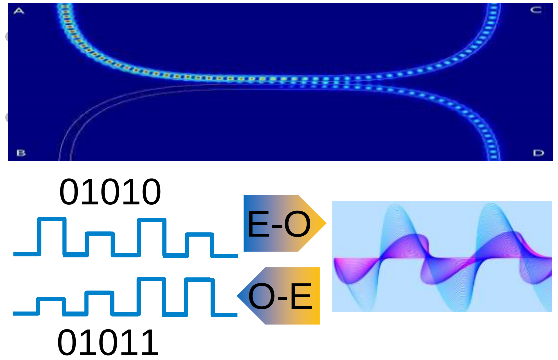
amf ADVANCED MICRO FOUNDRY
AIM photonics
SiEPIC
GlobalFoundries
tsmc
Tower Semiconductor

Gaps in Electronic-Photonic AI Eco-systems

- EPIC AI ecosystem is in *early* stage, many new challenges

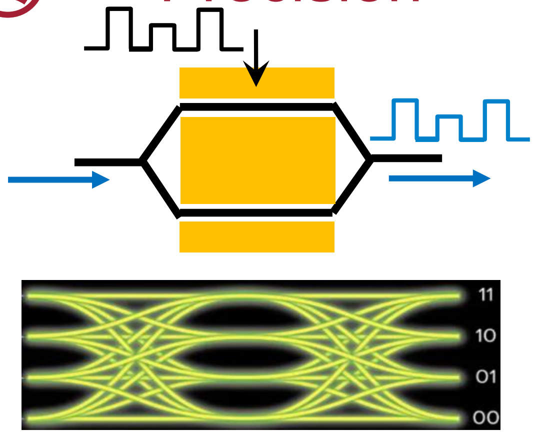
Area/E-O Cost

~40×200 μm^2



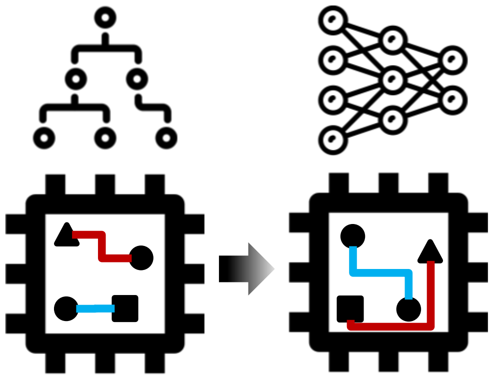
Large spatial footprint
E-O/A-D conversion

Precision



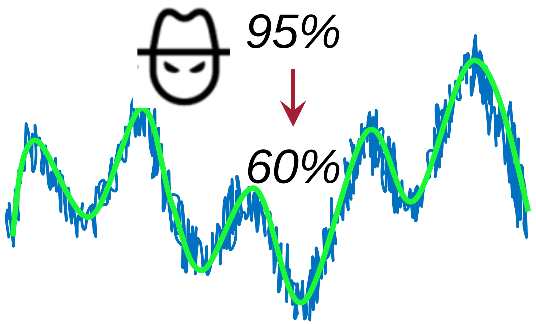
Low **precision** in encoding

Reconfigurability



Lack of **versatility** for diverse workloads

Reliability



Variations + **Attacks**
Accuracy loss

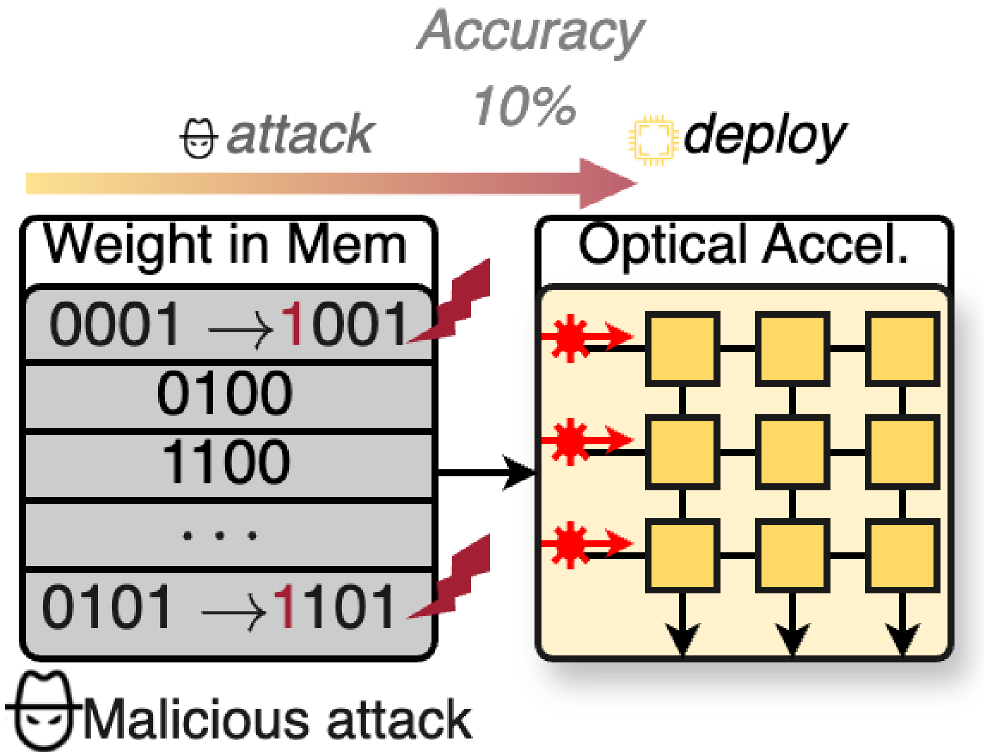
Our concern in this paper

??

Reliability is Severely Challenged by Attack

- **Security** problem is under-explored for AMS photonic AI hardware
- Serious reliability concerns with **<u>two</u>** enemies?

Malicious attack + Hardware non-ideality



Bit-flip Attack in Photonic AI Hardware

- Bit-flip (PBFA) [Rakin+, ICCV'19] poses great threat to Photonic AI HW
- White-box attack, arbitrary bit-flip available in model weights
- **First-order Gradient-based**, **Progressive**
  - Search the most vulnerable bit index to flip / iteration → largest acc. drop & loss

$$\min_{I_A} Acc\left(\widehat{W_{I_A}}; D^{test}\right) \approx \max_{I_A} \mathcal{L}\left(\widehat{W_{I_A}}; D^{attack}\right)$$
$$s.t. \left\|\widehat{W_{I_A}} - W\right\|_1 \leq HD;\ \#\ \text{model inf.} \leq T_{inf}$$

- *Hamming Distance* (HD) and *Inference Budget* (T_{inf}) constraint
- Hint: Attacks happen on **MSB mostly**

Threat Model

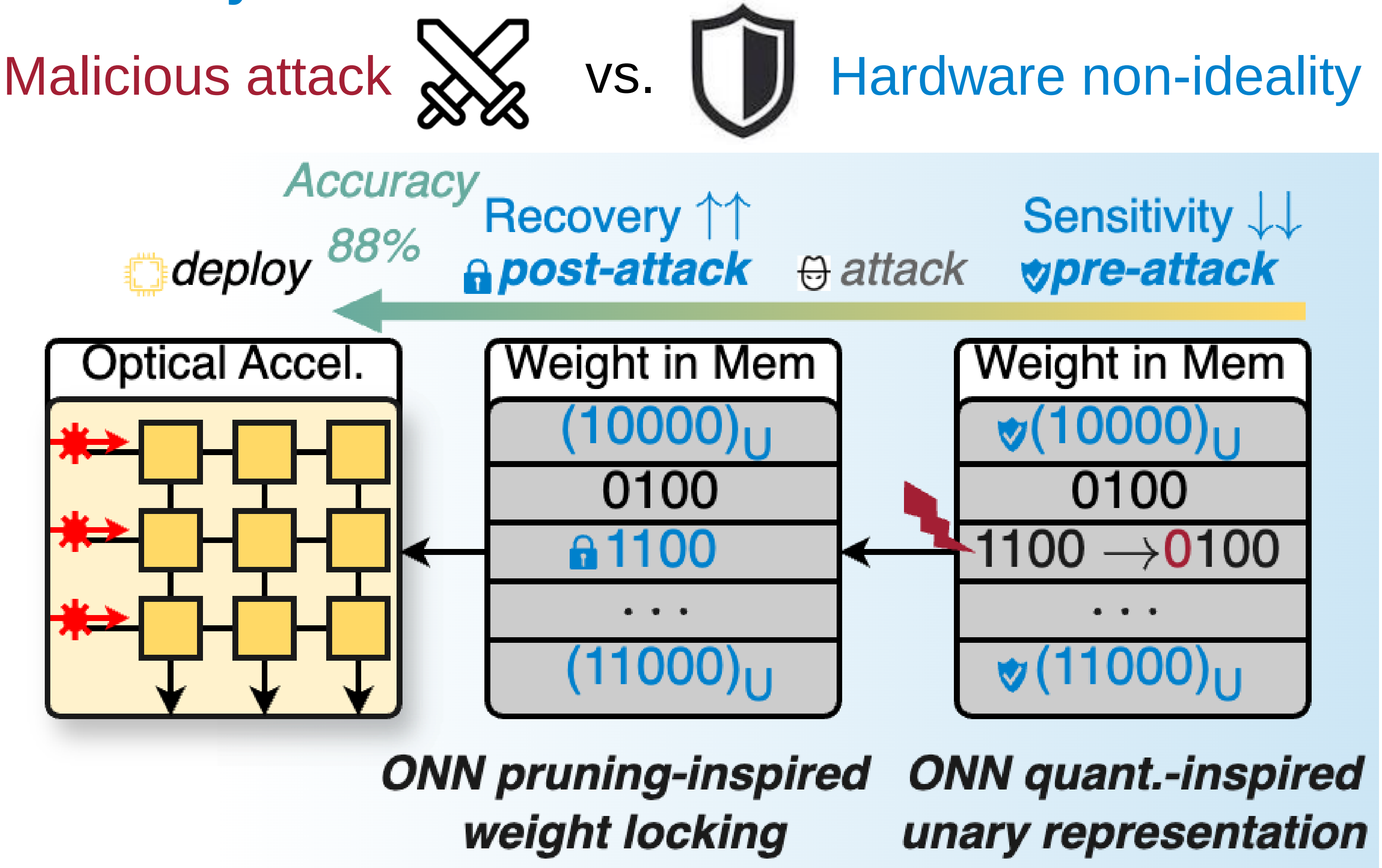
	Access Required	Access NOT Requied
	DNN model and parameters	Training Configurations
D^{attack} ←	A mini-batch of attack dataset	Modify scaling factors in quantization & Norm.
	On-chip forward/backward prop.	Modify address mapping/look-up tables

Prior Defense Methods for Photonic AI HW

<table>
<tr><th>Existing Defense v.s. Attack</th><th>NAT [Gu+,DATE’20]</th><th>BAT [He+, CVPR’20]</th><th>Pruning [Li+, DATE’21]</th><th>Common Challenges</th></tr>
<tr><td>Require Training?</td><td>Training-based</td><td>Training-based</td><td>Training-free</td><td rowspan="4">Either Pre- or Post-attack protection
Lack of effective while efficient defense framework targeted on photonic AI hardware
Novel defense method needs: <u>Training-free</u> + <u>Pre & Post Protection</u> + <u>High Mem. Efficiency</u> → <u>High Acc. Recovery</u></td></tr>
<tr><td>Occurance</td><td>Pre-attack</td><td>Pre-attack</td><td>Post-attack</td></tr>
<tr><td>Mem. Overhead</td><td>0</td><td>0</td><td>Relatively High</td></tr>
<tr><td>Recovery Performance</td><td>Low</td><td>Relatively High</td><td>Relatively High</td></tr>
</table>

Analog AI Accel. Nonideality: Double-edged Sword

- **Security** problem is un-explored for photonic AI hardware
- Insight: **Hardware nonideality can be built-in defender**
- Nonideality:
  - Quantization
  - Sparsity
  - On-chip Noise
  - etc …



Proposed Synergistic Defense Framework

1. Quantize-inspired Pre-attack Defense

- Protect via optics-specific *encoding*
- Memory efficiency optimization

+

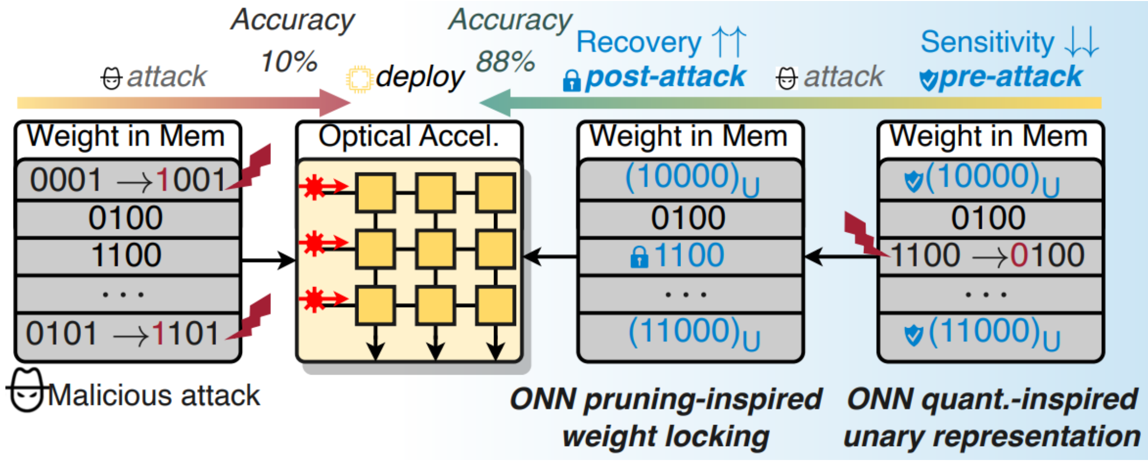
2. Prune-inspired Post-attack Recovery

- Efficient detection of bit-flipped weights
- Error correction via *weight locking*

=

Full Protection

- near-ideal acc. recovery (<2% drop)
- marginal memory cost (~2% ovhd)



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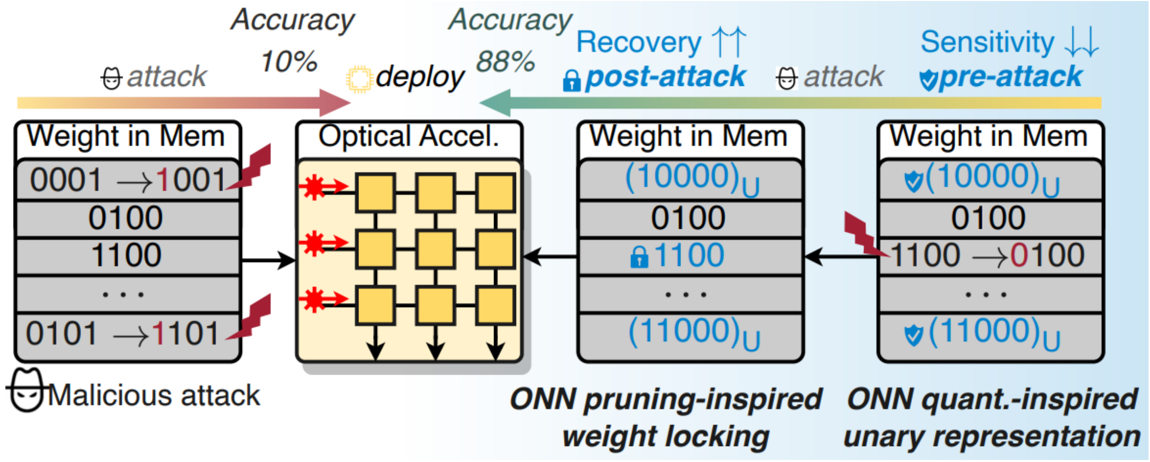
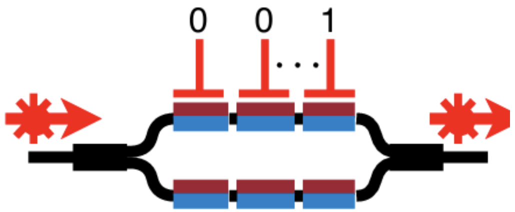
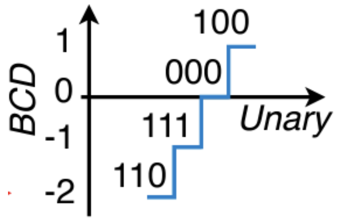


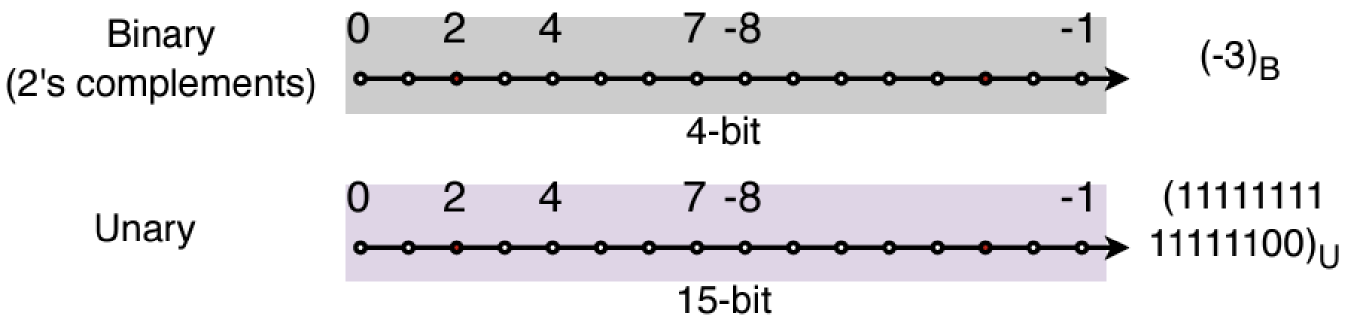
Minimize Weight Sensitivity by Unary Represent.

- **Electro-optic DAC**: unary encode → min sensitivity (LSB) → built-in defender

b bit BCD number W_B → $2^b - 1$ bit Unary number W_U $\boldsymbol{W_B = \#\ \mathbf{1s\ in\ W_U}}$: No MSB in W_U, **all LSB**







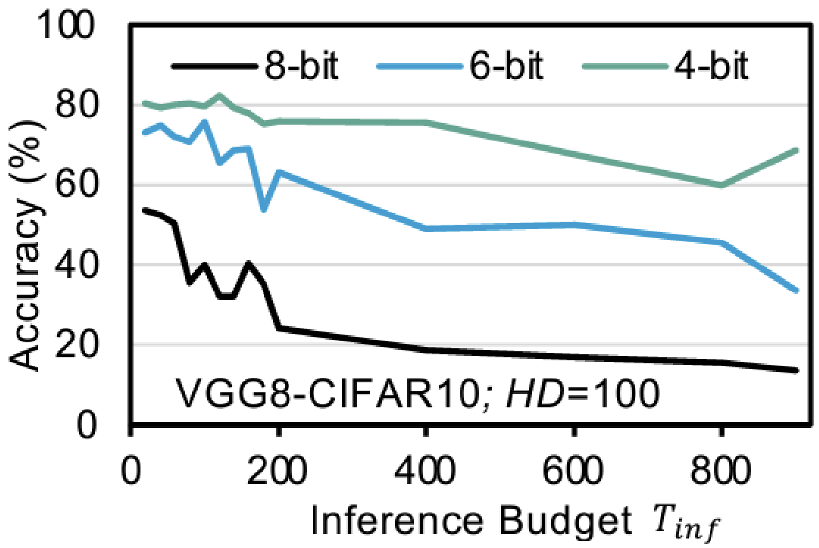
- **Exponential memory overhead...**

$$Mem_{OV} = \frac{2^b - 1}{b} \quad \longleftarrow \quad \approx 32 \times \text{OVHD for } b = 8\text{-bit}$$

How to reduce the memory overhead required by Unary Representation?

Memory-Efficient Unary Enc.: Low-bit Quant

- **Sol 1: Low-bit quantized model**
- Low-bit models are robust against attack
- Trade-off among (*mem-efficiency*, *robustness*, *expressivity*)

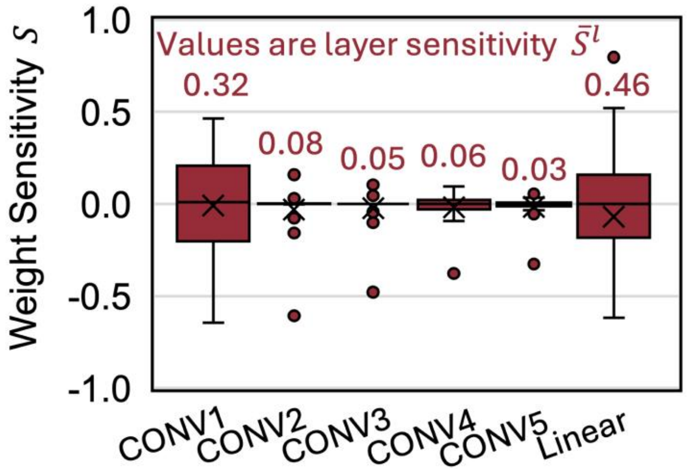


Memory-Efficient Unary Enc.: Vulnerable Weights

- **Sol 2: Only protect vulnerable weights**
- How to <u>identify</u> vulnerable weights?
  - Weight sensitivity represented by second-order Taylor Expansion
  - **Bitflip-injection** during sensitive weight search

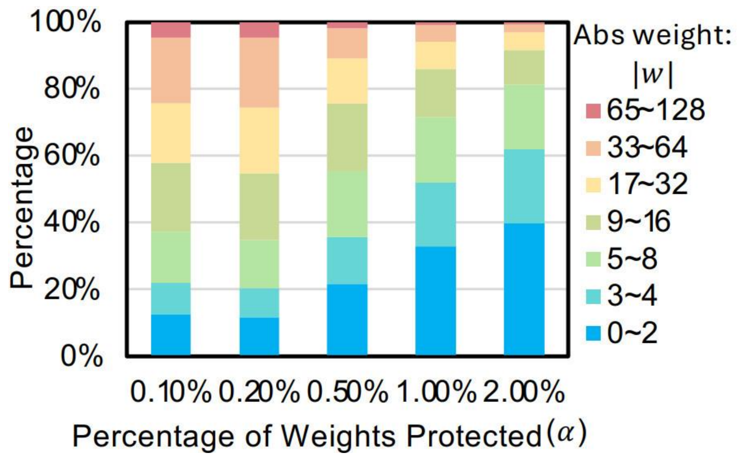
$$S = \nabla_W \mathcal{L} \cdot \Delta W_{MSB} + \frac{1}{2} \nabla_W^2 \mathcal{L} \cdot \Delta W_{MSB}^2$$

- How to <u>assign</u> limited memory budget?
  - **Uneven** sensitivity distribution in layers
  - **Top-Sensitive-Layer Assignment** for given mem. budget α: <u>Fill most sensitive first!</u>



Memory-Efficient Unary Enc.: Fold & Truncation

- **Sol 3: Fold & Truncate the encoding**
- Observation: Sensitive weights have small abs values (**Gaussian-like** Distribution)
  - *Waste* to store trailing 0s

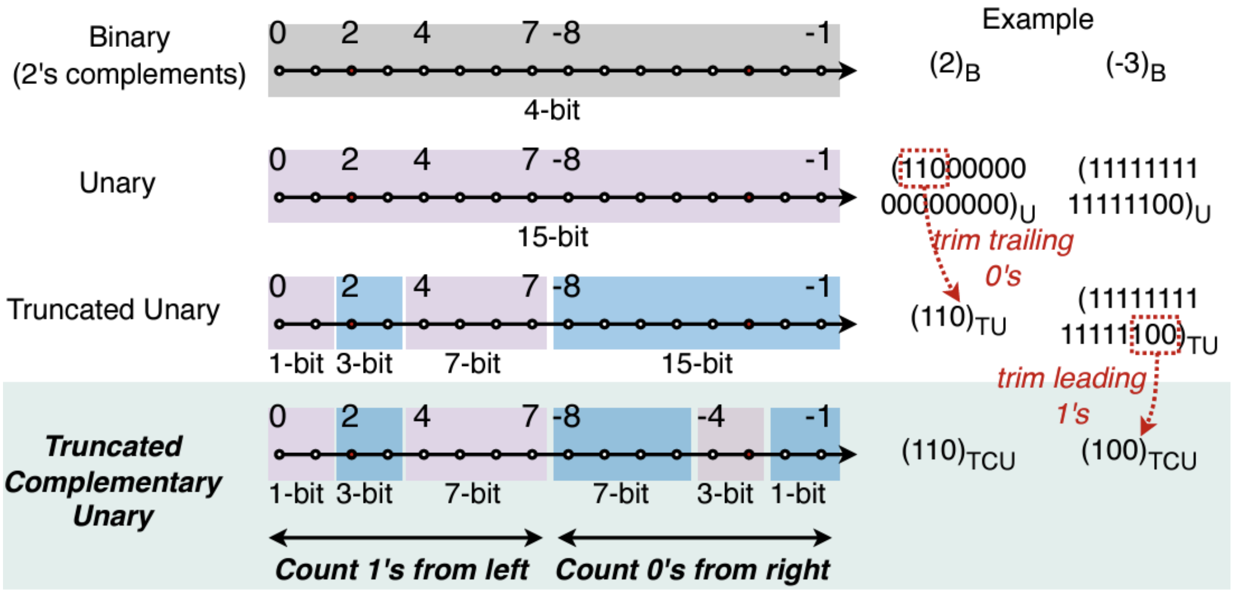


- **Truncate** unnecessary 0s to bins (TU)

  $(W)_U$: $2^b - 1$ bit → $(W)_{TU}$: $2^{\lceil \log_2 |W| \rceil} - 1$ bit
  - Negative values still take large #bits

- **Fold** symmetric encoding (TCU)
  - pos.: count 1's; neg.: count 0's
  - Truncated **Complementary** Unary

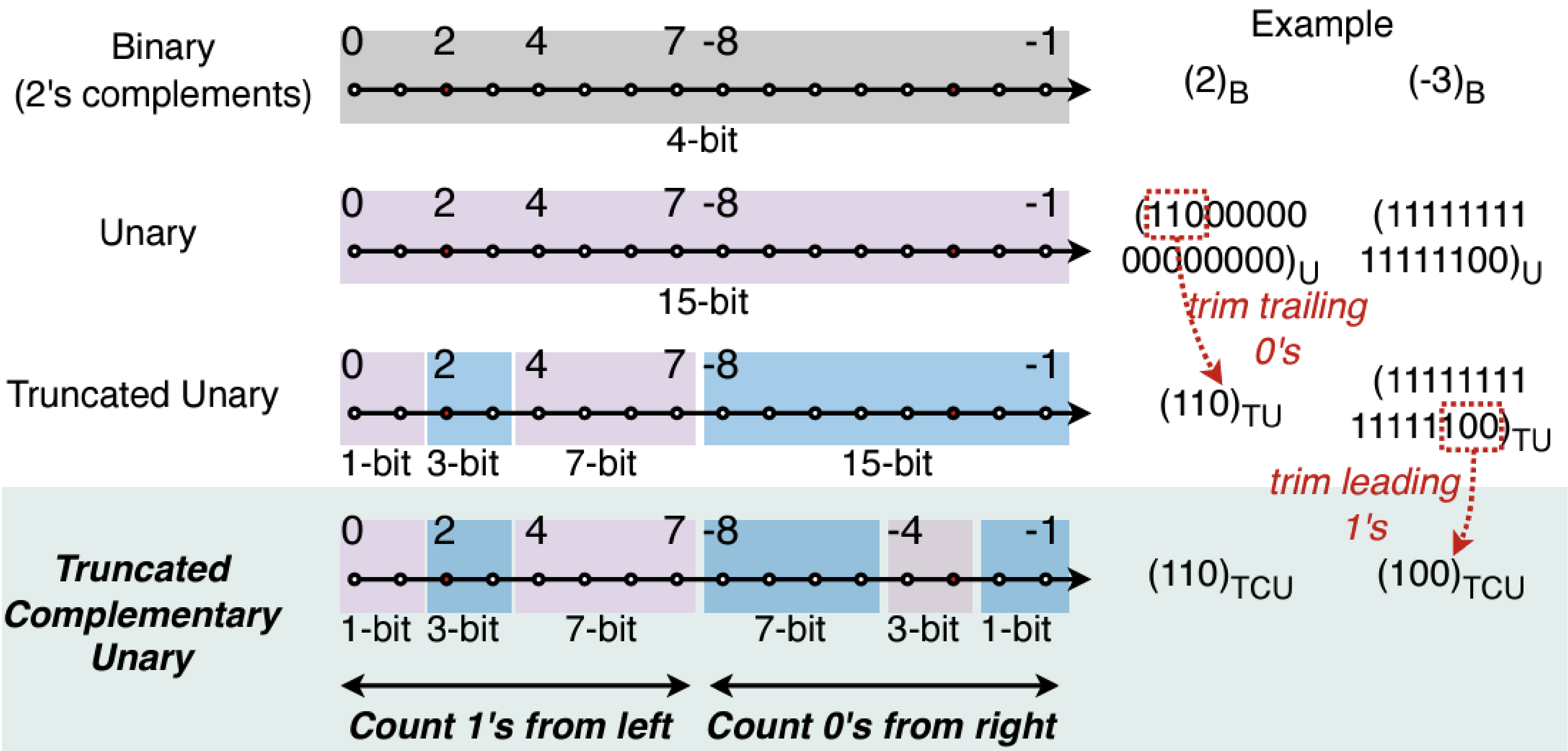
$(W)_U$: $2^b - 1$ bit → $(W)_{TCU}$: $2^{\lceil \log_2 \min\{|W|, |2^b - W|\} \rceil} - 1$ bit



Quantization-Inspired: Pre-deploy Protection

- Truncated complementary unary (TCU) + protect ***vulnerable*** weights
- Attack-injected Weight Protection Search for ***vulnerable*** weights

  → mem.-efficient & secure



Pre-deploy provides ***insufficient target-less*** protection.

How to compensate for potential protection miss?

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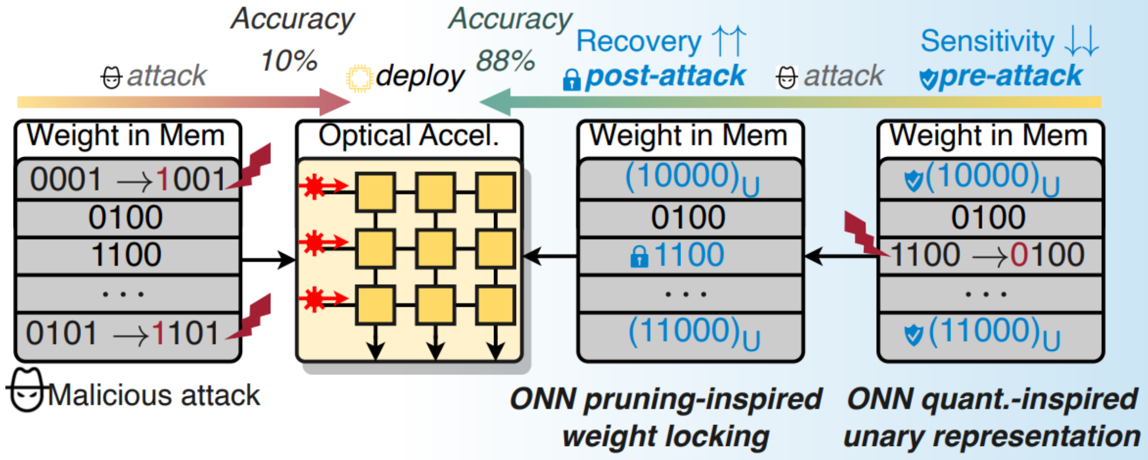
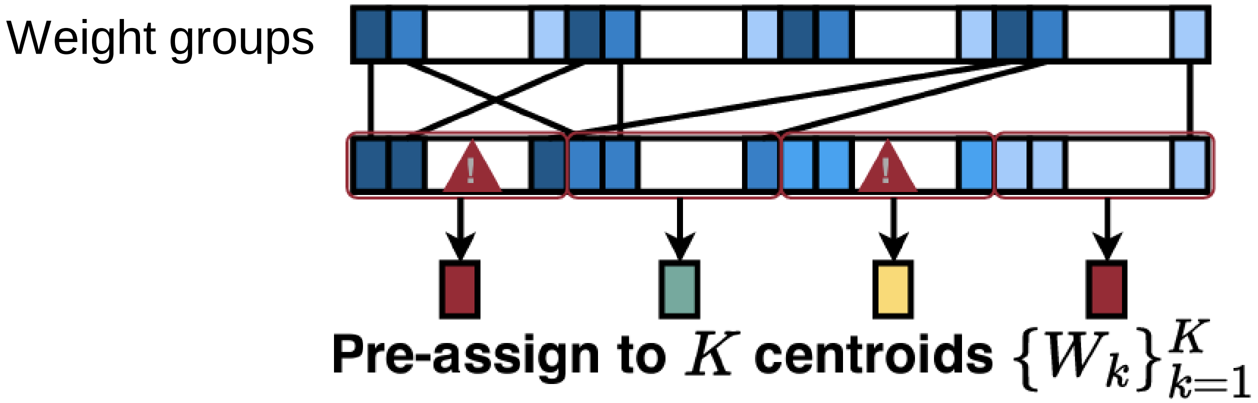


Group-based Detection: Checksum

- Post-deploy protection: detect → correct
- **Detection** of Attacked Weights
  - Interleaving weight group, layer-wise
  - MSB checksum verification [Li+, DATE'21]
  - 2-bit checksum for a group of G Weights

    → **Pinpoint MSB-targeted attacks with high coverage**

    (might miss attacked weights; cannot localize specific weight in a group)
- How to correct detected weights?
  - No access to original values anymore…
  - → assign a value to wipe out attacks (prior work prunes it to 0, not good, like self-attack…)



Which values should we assign?
(Trade off accuracy vs. robustness)

Preparation for Group-based Weight Recovery

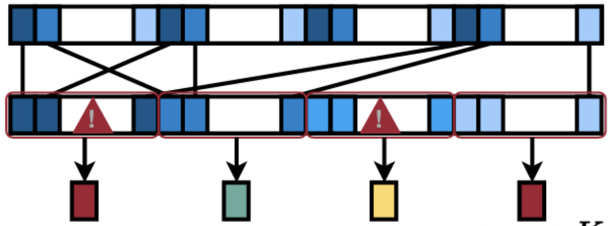
- Smart values to assign: group centroid
- Sensitivity-aware cluster centroids
  - Total **K** clusters in $\widetilde{W}$ (cluster size: **G**)
  - K-Means clustering $\{\widetilde{W}\}$ → K centroids $\{\widetilde{W}_K\}$
  - Assign one centroid $\widetilde{W}$ → each group

- How to make it attack-aware?
  - Sensitivity-aware distance in K-means

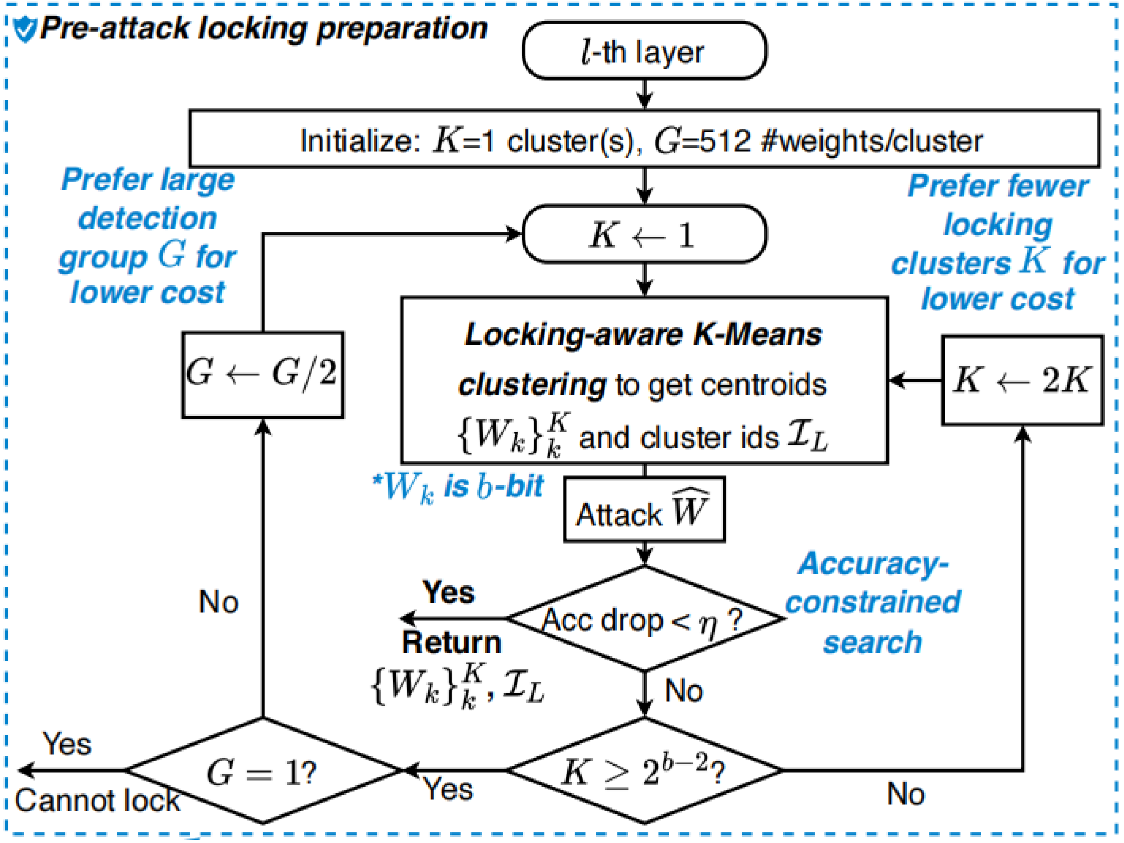
$$\min_{\widetilde{W}} \sum_{i=1}^{G} d_i = \sum_{i=1}^{G} \nabla_W \mathcal{L} \cdot (W_i - \widetilde{W}) + 0.5 \cdot \nabla_W^2 \mathcal{L} \cdot (W_i - \widetilde{W})^2$$

  - Attack injection to evaluate post-attack acc.

- How to make it memory-efficient?
  - Prefer **larger G** and **smaller K** for lower cost



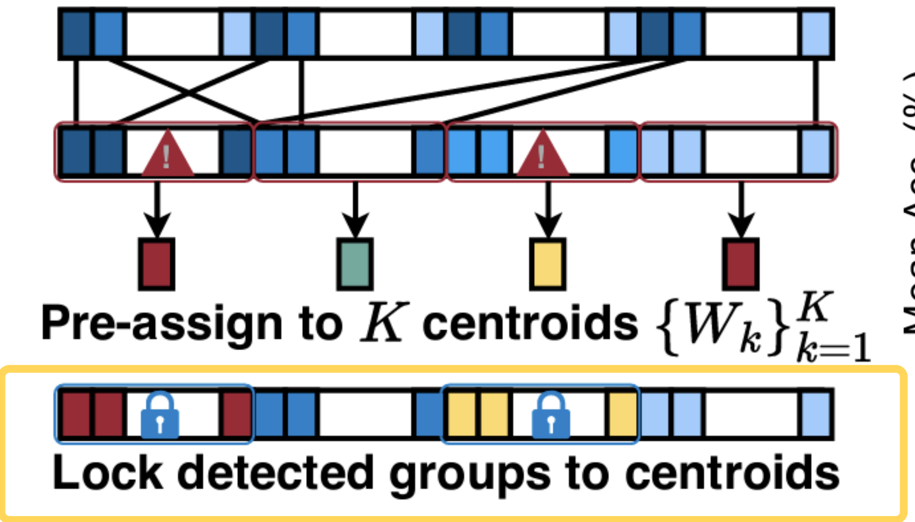
Pre-assign to K centroids $\{W_k\}_{k=1}^{K}$

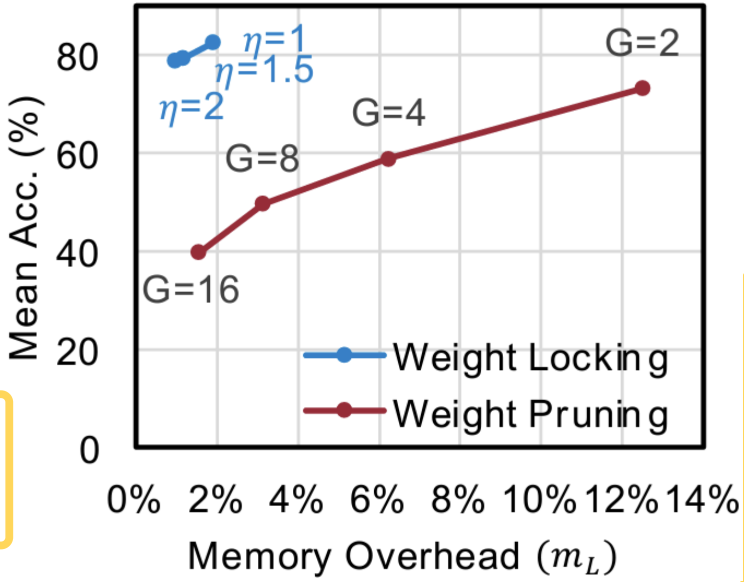


Proposed Weights Grouping and Vulnerability-aware Clustering

Pruning-Inspired: Post-deploy Recovery

- **Pruning-Inspired** protection → weight locking
- Smartly group weights and lock to centroids (vulnerability-aware K-Means)
  → ***wipe*** attacked weights & maintain acc & mem-efficient





Locking provides less "self-attack" compared with Pruning
→ ***Larger G, less mem. overhead***

Insight
- "Pruning" wipes out attack
- Locking generalizes pruning
- Low overhead but w/ acc cost

Synergistic Pre-/Post-Deploy Protection

Quantize-inspired unary encoding (eoDAC)
→ min sensitivity (LSB) → built-in defender

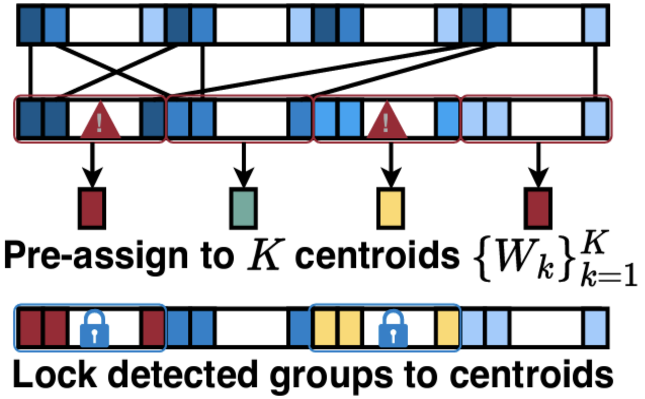
Binary (2's complements)	$(2)_B$	$(-3)_B$
Truncated Complementary Unary	$(110)_{TCU}$	$(100)_{TCU}$

Insight

- Low-bit model is more robust to attack
- Statistics-aware unary encoding balances *memory vs. security*

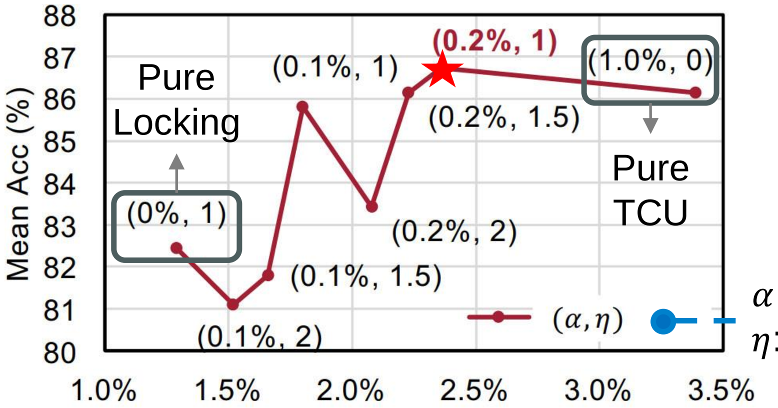
✚

Pruning-inspired weight locking
→ group&lock attacked weights to centroids



Insight

- "Locking" wipes out attack
- Low mem. overhead at small acc. drop



α: Protect. ratio of TCU
η: Accep. Acc. Drop of Locking

★ ***Optimal Mem. budget allocation***

Large mem. for TCU +
small mem. for Weight Locking

Train-Free Memory-Efficient Build-in Defender

- Prior methods (Noisy train/Quantize/Prune): only 25~80% acc w/ 3 hr train cost
- **Our method: 83~86.7% acc @ 2% memory overhead w/ <1 hr search**
- Provide **Near-ideal Accuracy Recovery** with **Marginal** Memory Budget

Category	Quant. Bit	Defense Method	Prior-attack Accuracy	Worst Acc.	**Mean Acc.**	Training/Searching Runtime	Memory Overhead Pre (m_{TCU})	Post (m_L)	Total
w/o Def	4-bit	-	87.73	59.87	75.85	-			
	6-bit	-	88.00	33.58	61.74				
	8-bit	-	88.00	13.52	32.89				
Training-based	1-bit	BAT [19]	87.09	74.62	80.39	0.33 hrs	-		
	4-bit	NAT [10]	87.96	66.71	77.06	2.8 hrs			
	6-bit	NAT [10]	87.19	33.39	64.78	2.8 hrs			
	8-bit	NAT [10]	85.91	26.14	55.88	2.8 hrs			
Training-free	4-bit	Pruning [19]	87.73	57.23	70.68	-	3.13% (G=16)		
		Ours	87.73	83.08	**84.74**	0.03hrs + 0.33 hrs	0.84%	0.000%	0.84%
	6-bit	Pruning [19]	88.00	40.74	66.14	-	4.17% (G=8)		
		Ours	88.00	86.25	**86.48**	0.03hrs + 0.50 hrs	0.93%	1.11%	2.04%
	8-bit	Pruning [19]	88.00	18.68	48.59	-	3.13% (G=8)		
		Ours	88.00	86.08	**86.73**	0.03hrs + 0.75 hrs	1.07%	1.29%	2.36%

Model: VGG8, Dataset: Cifar-10

Open-Source
ONN Defender

ONN Defender against Adversarial Attacks

Thank you!
Q & A?

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