Towards Memory-Efficient Neural Networks via Multi-Level in situ Generation

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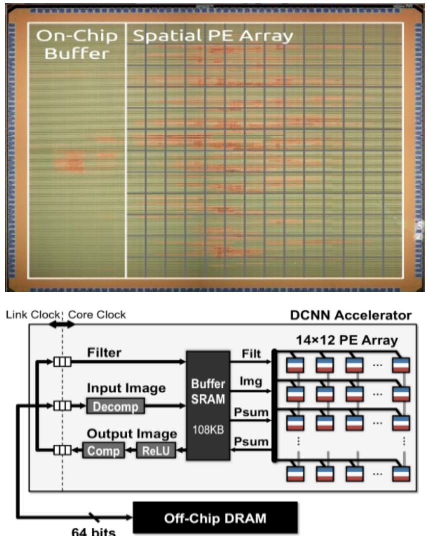
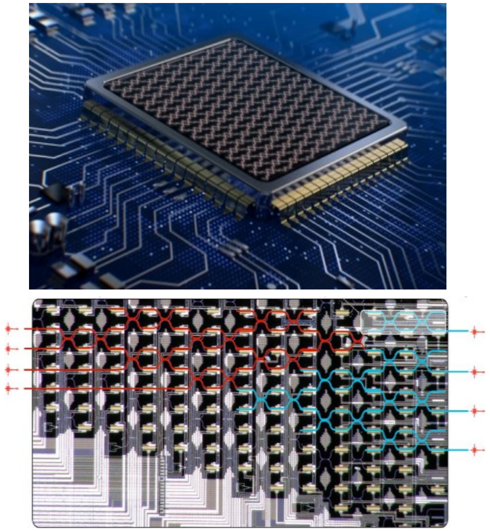
Efficient On-Device AI

- ML models/dataset keep increasing -> more computing capacity/efficiency
  - Low latency
  - Low power
  - High bandwidth

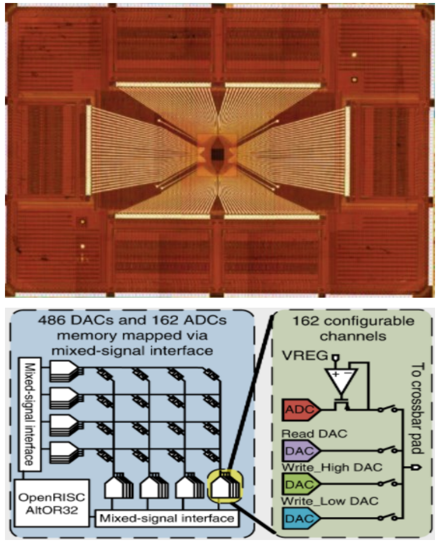
- Extensive efforts on efficient AI solutions



[Eyeriss, *ISSCC'2016*]
Electrical Digital



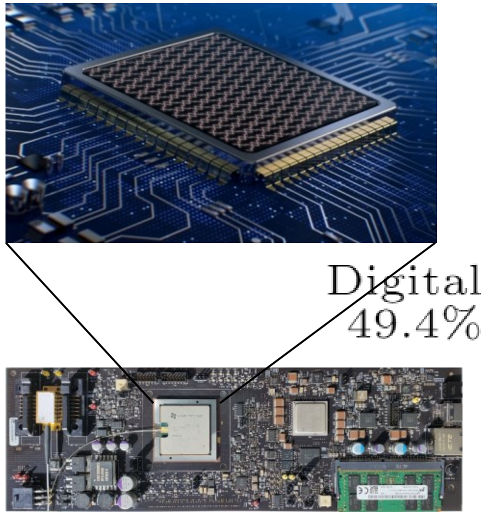
[Mars, *NaturePhotonics'2017*]
Photonics Analog

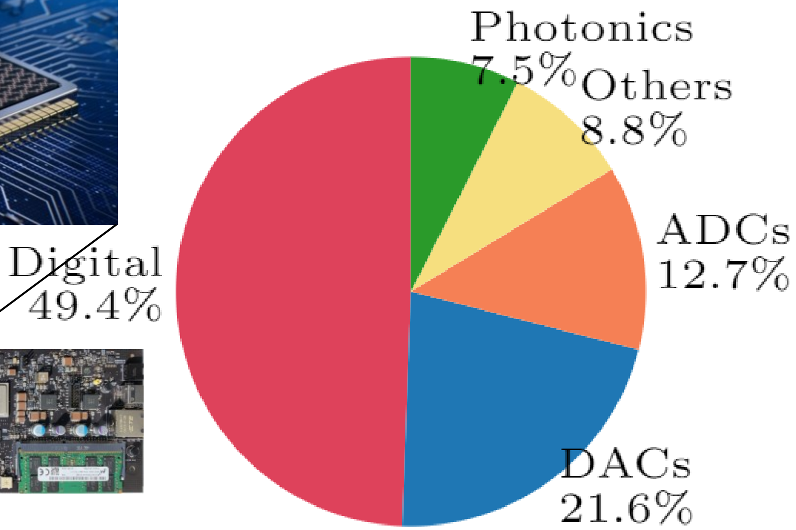


[ReRAM Xbar, *NatureElectronics'2019*]
Electrical Analog

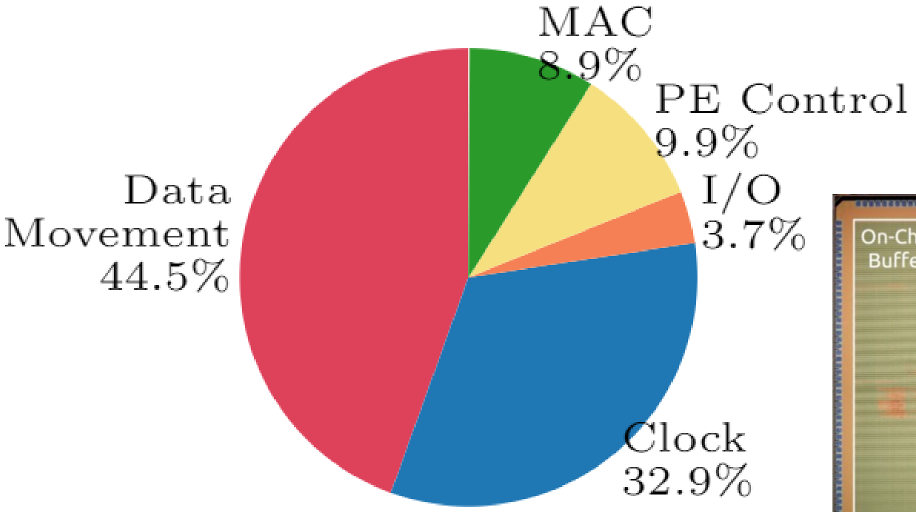
Challenges: Data Movement Bottleneck

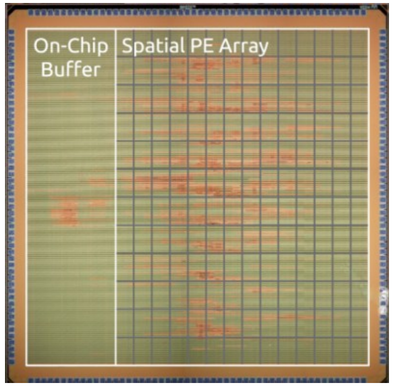
- Power consumption is mainly on memory storage/access
  - SRAM vs. Optical MVM: 50% vs. 8%
- Latency/performance is bottlenecked by data movement
  - SRAM: >10 ns and ~300 GB/s
  - Optical MVM: ~100 ps and ~3×10^6 GLOPS





[Mars, *NaturePhotonics'2020*]
Photonics Analog

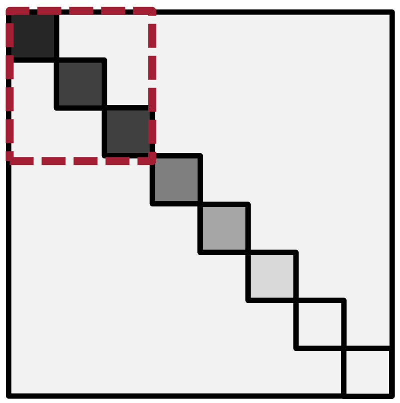


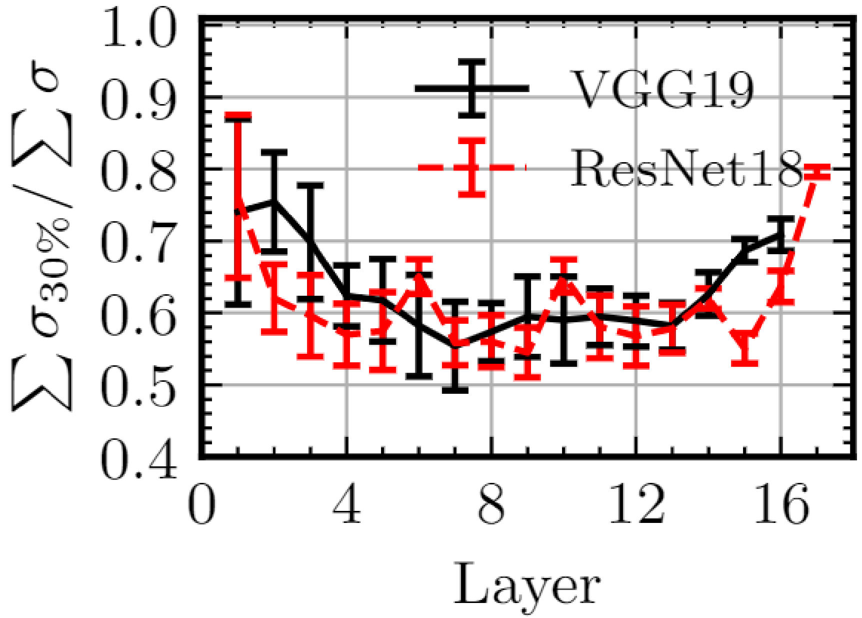


[Eyeriss, *ISSCC'2016*]
Electrical Digital

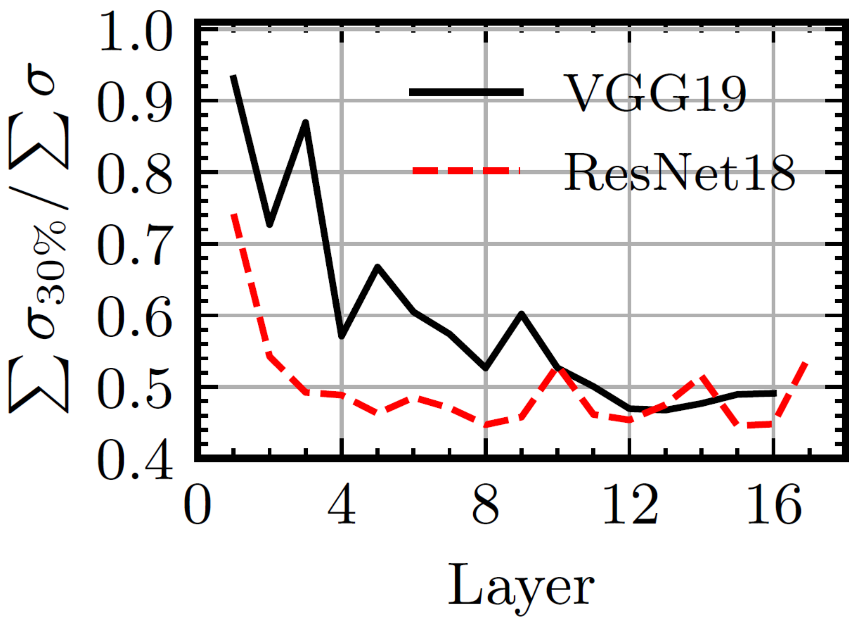
Opportunity: Multi-Level Redundancy in DNNs

- Observation of weight correlation via SVD
  - Intra-kernel correlation
  - Cross-kernel correlation
  - 50-90% total values on 30% top singular values





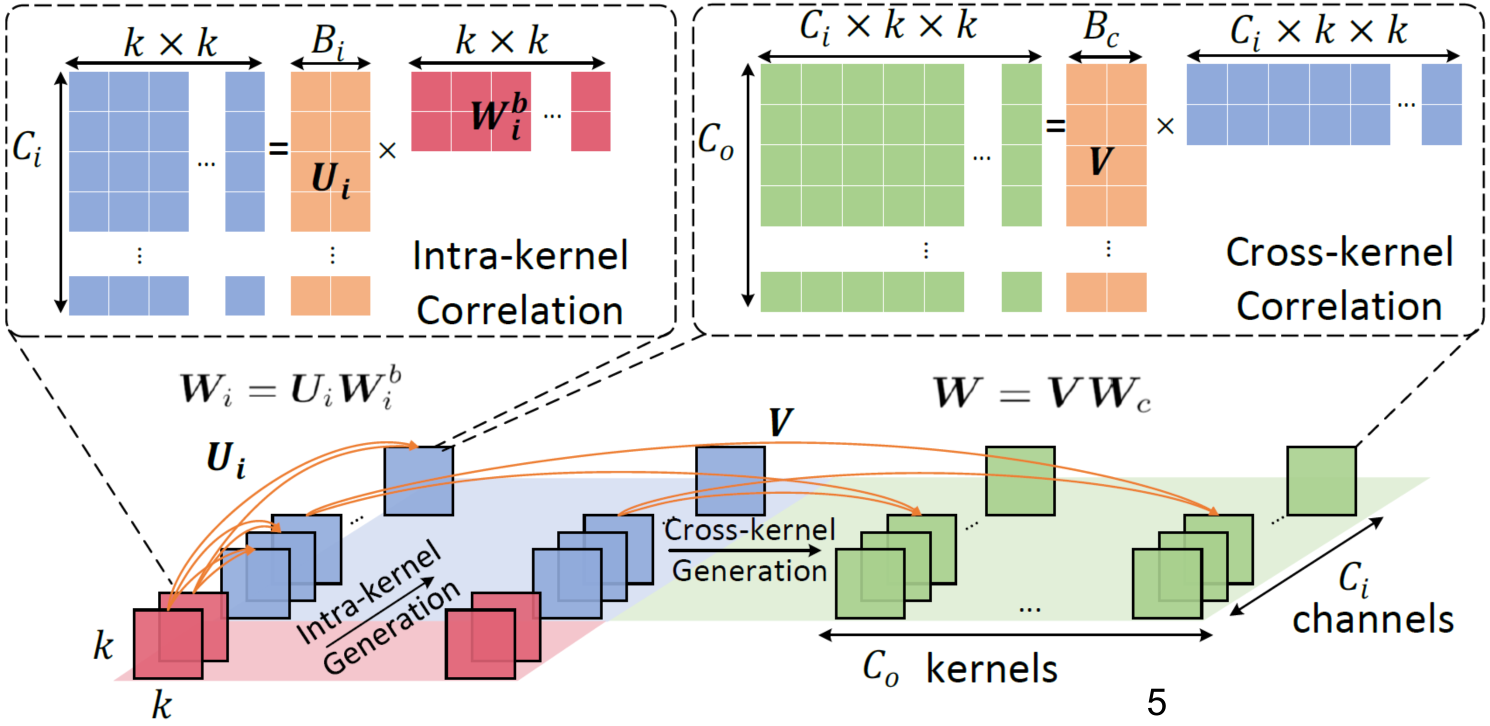
Intra-kernel correlation

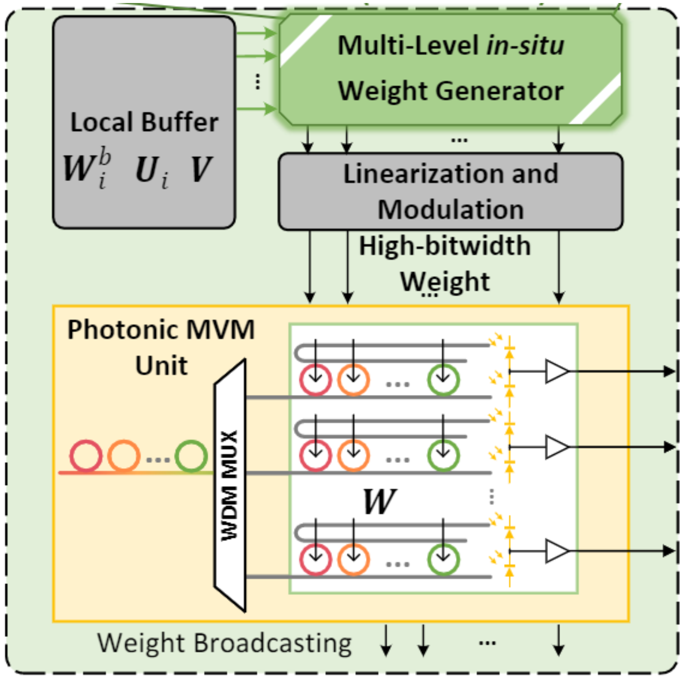


Cross-kernel correlation

Our Method: Multi-Level *in situ* Generation

- Trade expensive data movement for cheap computations
- A unified framework to generalize prior single-level low-rank NNs
- Kernel redundancy: Intra-/cross- kernel generation on-the-fly
- Bit-level redundancy: Precision-preserving mixed-precision basis





Proposed Memory-Efficient ONN Design

Explore Kernel Redundancy

- Intra-kernel generation (B_i)
  - Span all input channels from a small basis $\boldsymbol{W}^b$

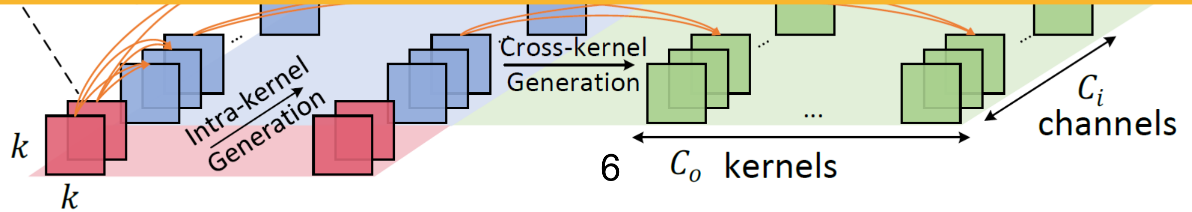
$$\boldsymbol{W}_i = \boldsymbol{U}_i \boldsymbol{W}_i^b, \quad \forall i \in [C_o]$$

- Cross-kernel generation (B_c)
  - Span all kernels from a kernel basis

$$\boldsymbol{W} = \boldsymbol{V} \boldsymbol{W}_c = \boldsymbol{V} \{\boldsymbol{U}_i \boldsymbol{W}_i^b\}_{i \in [B_c]}$$

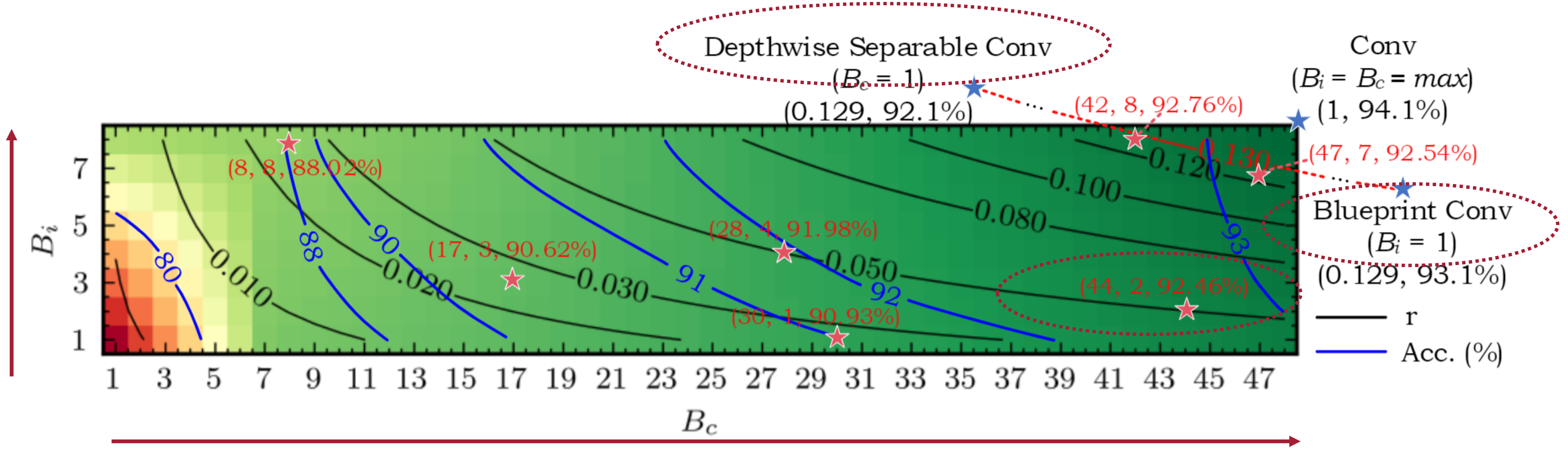
Params. reduction ratio

$$r = \frac{|\boldsymbol{V}| + \sum_{i \in [B_c]} (|\boldsymbol{U}_i| + |\boldsymbol{W}_i^b|)}{|\boldsymbol{W}|} = \frac{(C_o + B_i k^2 + C_i B_i) B_c}{C_o C_i k^2}$$



Performance/Efficiency Contour

- Explore the multi-level generation space
  - Generalize separable CONV [He+, *CVPR*'16] and Blueprint CONV [Haase+, *CVPR*'20]
  - **Small B_i + Medium B_c** → Good efficiency and performance trade-off



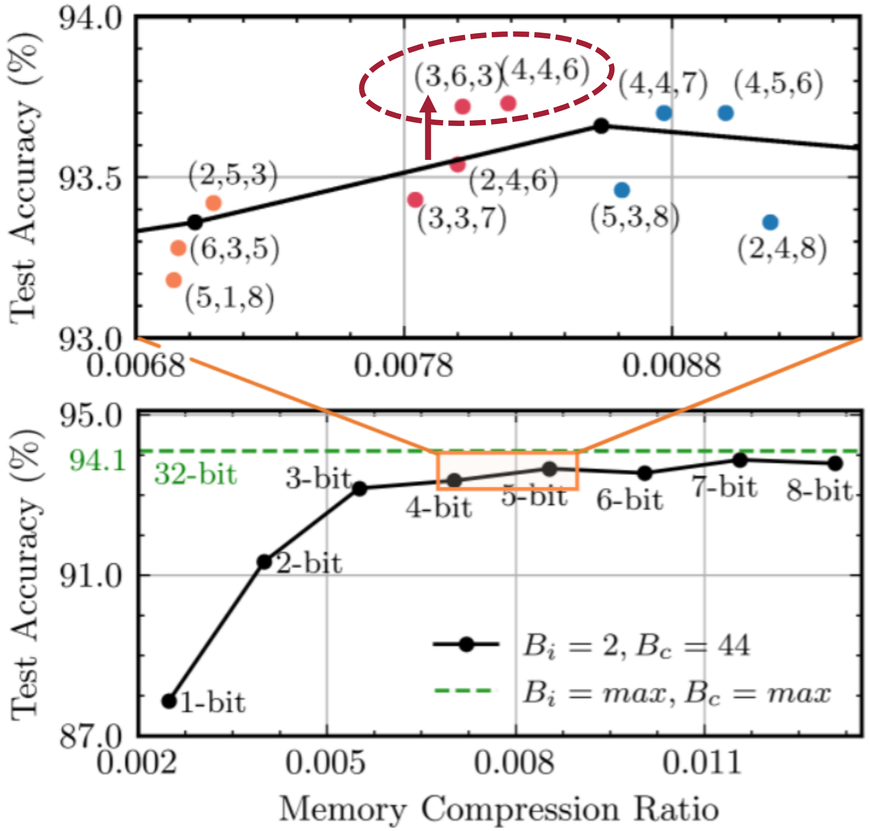
Explore Bit-Level Redundancy

- Augmented mixed-precision kernel generation
- Assign different bits to basis and coefficients

$$(q_b, q_u, q_v) \rightarrow (\boldsymbol{W}_b, \boldsymbol{U}, \boldsymbol{V})$$

- Precision-preserving using analog generators

$$\sup(q_c) = (q_b + q_u + \log_2 B_i)$$
$$\sup(q) = (q_v + \sup(q_c) + \log_2 B_o)$$



Memory compression ratio

$$r_m = \frac{B_c B_i k^2 q_b + B_c C_i B_i q_u + C_o B_c q_v}{C_o C_i k^2 q_w}$$

Effective Training Flow for in-situ Generation

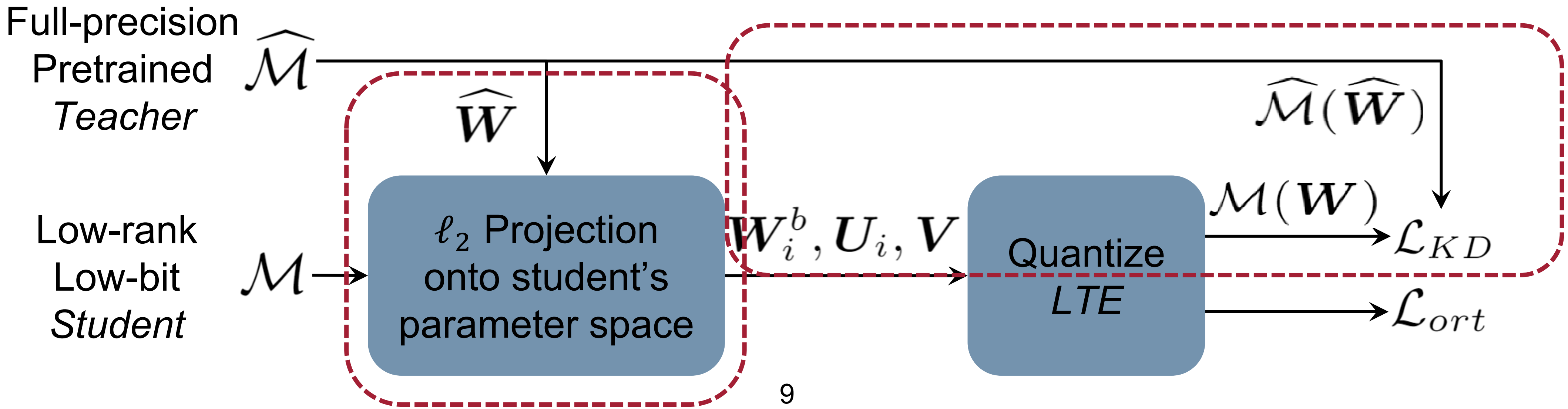
- Project teacher to student parameter space

$$\boldsymbol{W}_i^b, \boldsymbol{U}_i, \boldsymbol{V} \leftarrow \operatorname{argmin} \ \|\widehat{\boldsymbol{W}} - \boldsymbol{V}\{\boldsymbol{U}_i \boldsymbol{W}_i^b\}_{i \in [B_c]}\|_2^2$$

- Quantization-aware knowledge distillation to guide optimization

$$\min \ \mathcal{L}_{KD} = \beta T^2 \mathcal{D}_{KL}(q_T, p_T) + (1-\beta) H(q, p_{T=1})$$

$$\text{s.t. } \ p_T = \frac{\exp(\frac{\mathcal{M}(\boldsymbol{W})}{T})}{\sum \exp(\frac{\mathcal{M}(\boldsymbol{W})}{T})}, q_T = \frac{\exp(\frac{\widehat{\mathcal{M}}(\widehat{\boldsymbol{W}})}{T})}{\sum \exp(\frac{\widehat{\mathcal{M}}(\widehat{\boldsymbol{W}})}{T})},$$

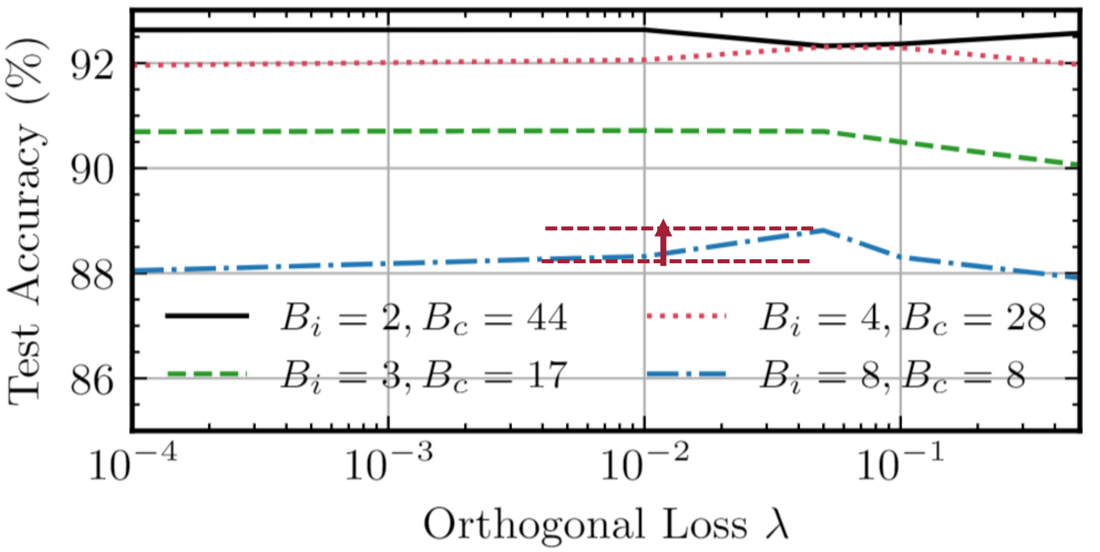


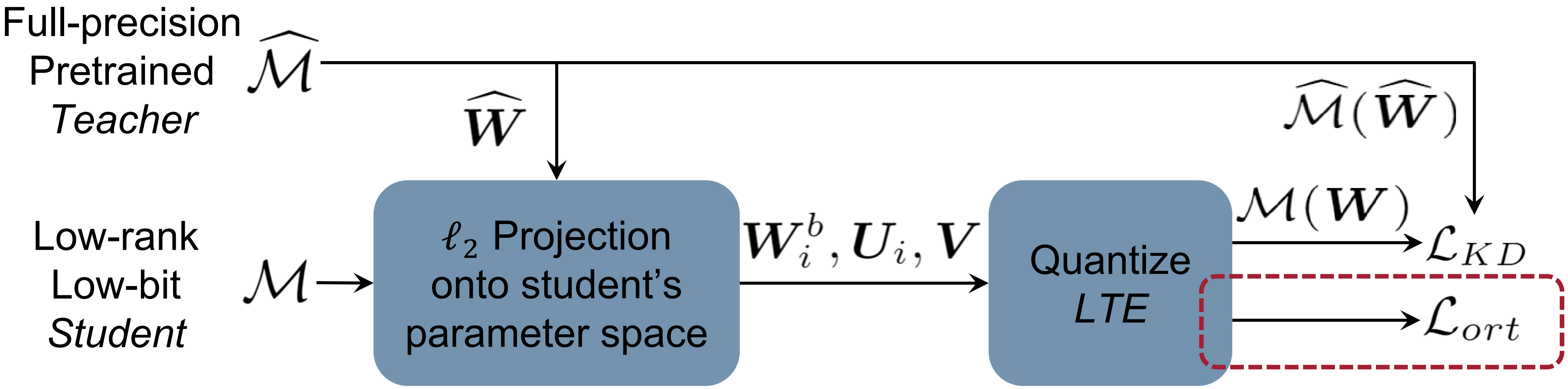
Effective Training Flow for in-situ Generation

- Encourage the rank of spanned kernel
- Multi-level orthonormality regularization

$$\sum_{i=1}^{B_c}\left(\|\boldsymbol{W}_i^b(\boldsymbol{W}_i^b)^T-\boldsymbol{I}\|_2^2+\|\tilde{\boldsymbol{U}}_i^T\tilde{\boldsymbol{U}}-\boldsymbol{I}\|_2^2\right)+\|\tilde{\boldsymbol{V}}^T\tilde{\boldsymbol{V}}-\boldsymbol{I}\|_2^2,$$

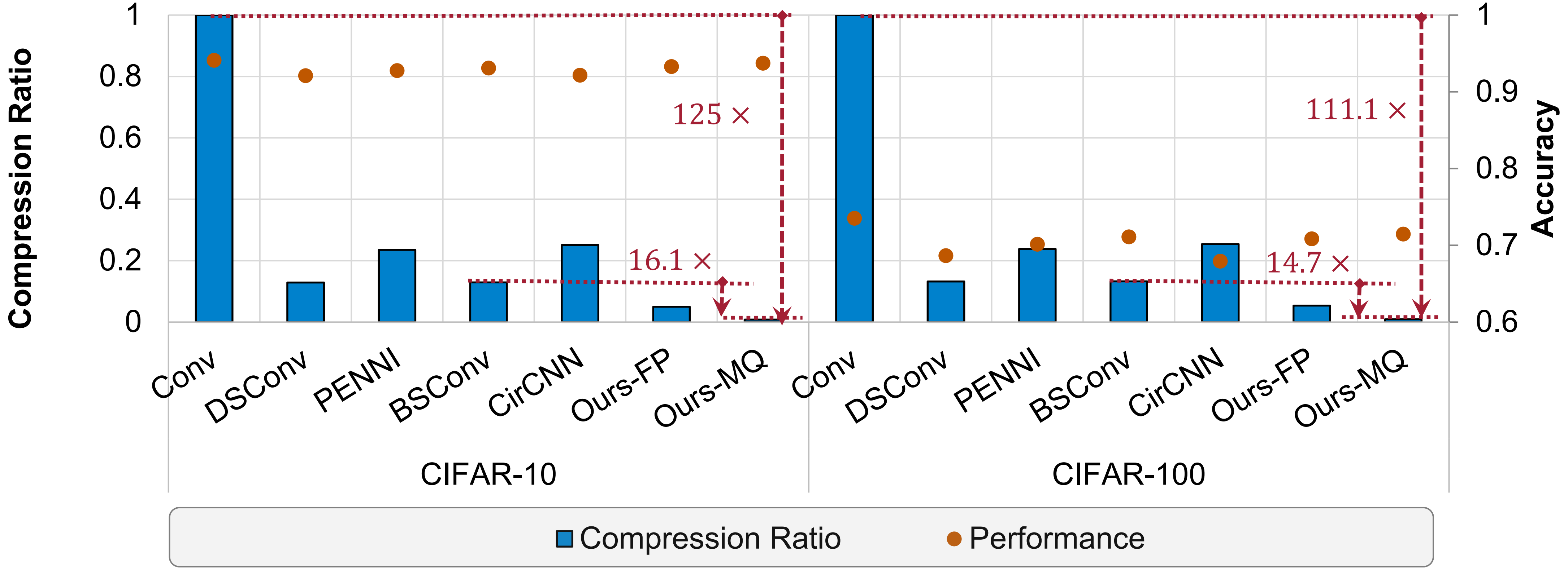
$$\tilde{\boldsymbol{U}}_i=\left(\frac{u_0}{\|u_0\|_2^2}\cdots\frac{u_0}{\|u_{B_i-1}\|_2^2}\right),\tilde{\boldsymbol{V}}=\left(\frac{v_0}{\|v_0\|_2^2}\cdots\frac{v_0}{\|v_{B_c-1}\|_2^2}\right)$$





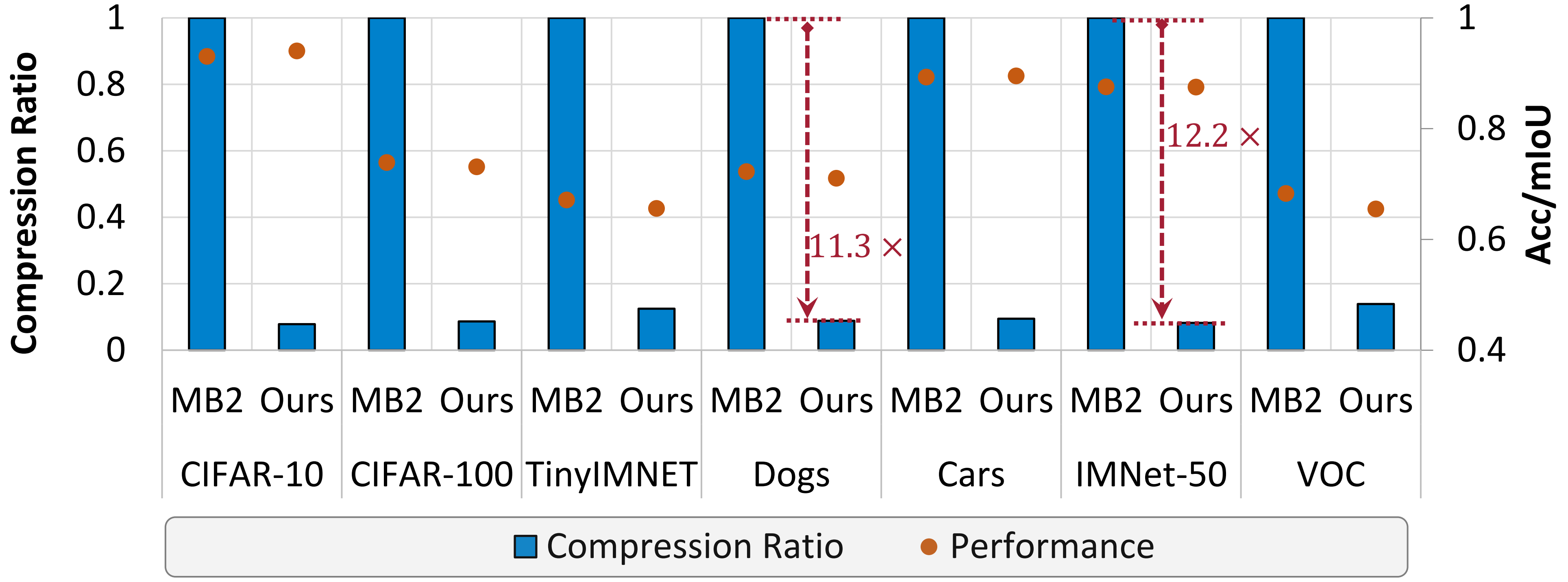
Experimental Results

- ResNet-18 + CIFAR10/100
  - **>100×** memory cost reduction on baseline architecture
  - **~15×** more efficient and **0.5%** higher accuracy than best baselines



Experimental Results

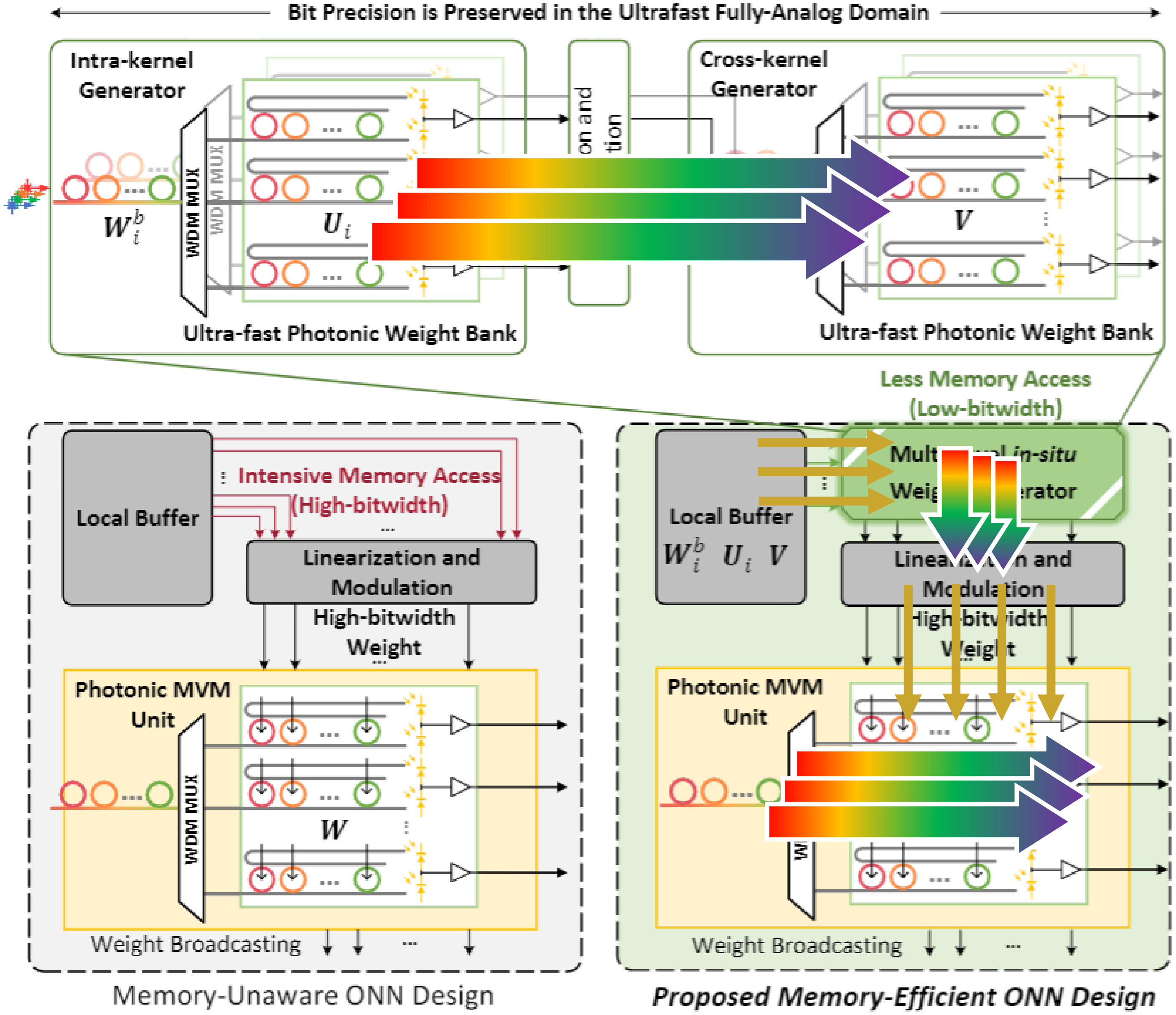
- MobileNetV2 + Various vision benchmarks
  - **>10×** memory cost reduction on *compact* architecture
  - Marginal performance drop on classification and object detection



Photonics NN Simulation

- Photonic MVM cores
- Ultra-fast optical weight generator

- ResNet-18/ImageNet
- Latency (**27.2%** ↓)
  - 56.46 ms → **41.11** ms
- Energy (**85.7%** ↓)
  - 25.77 mJ → **3.69** mJ
- Energy-delay product (**9.6**× ↓)



Conclusion and Future Work

- A unified multi-level in-situ generation framework for memory-efficient NNs
- **10~100× compression**: channel-level + kernel-level + bit-level
- **<1% performance drop**: projection + distillation + ortho regularization
- **~10× energy-delay reduction**: ultra-fast generator on emerging accelerators

- Future work
  - Automatic search of per-layer cardinality and mixed precision settings
  - Sparsity exploration on the in-situ generation

Thank you

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