ROQ: A Noise-Aware Quantization Scheme Towards Robust Optical Neural Networks with Low-bit Controls

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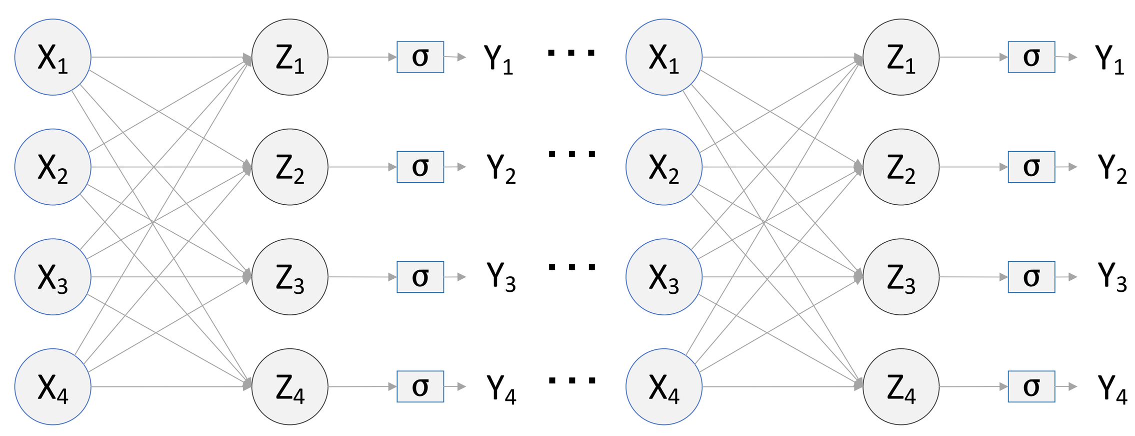
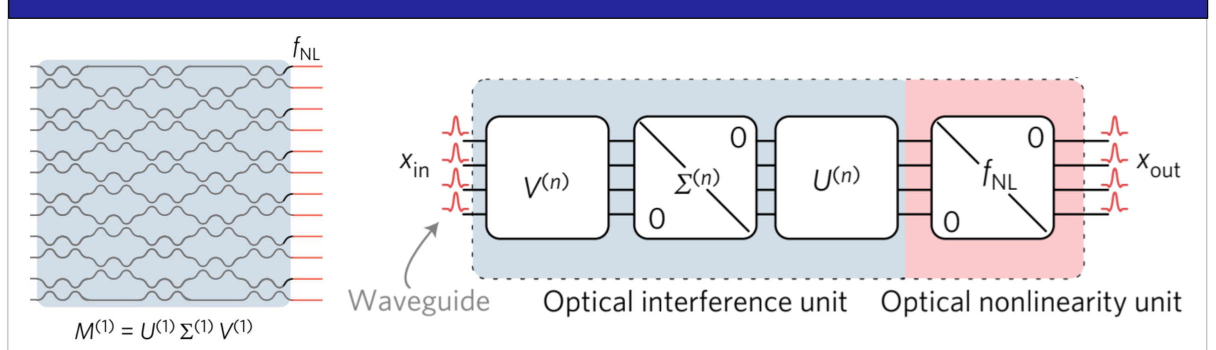
Multi-layer Perceptron Inference

- Input
  - Vector $\boldsymbol{x}$
- Output
  - Vector $\boldsymbol{y} = \sigma(\boldsymbol{W} \cdot \boldsymbol{x})$
- Objective
  - Accuracy

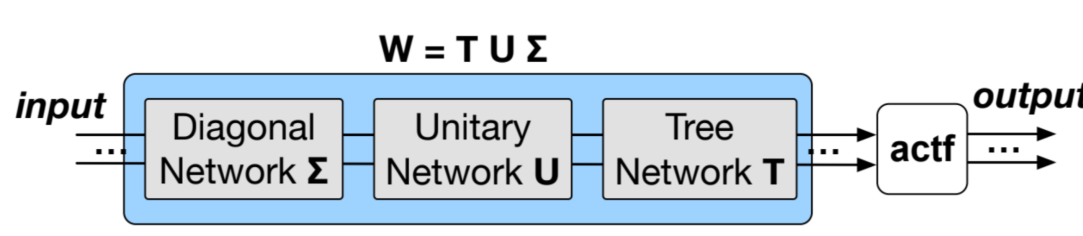


ONN Architectures



- SVD-based ONNs with MZIs

[Nature'17, Shen+]

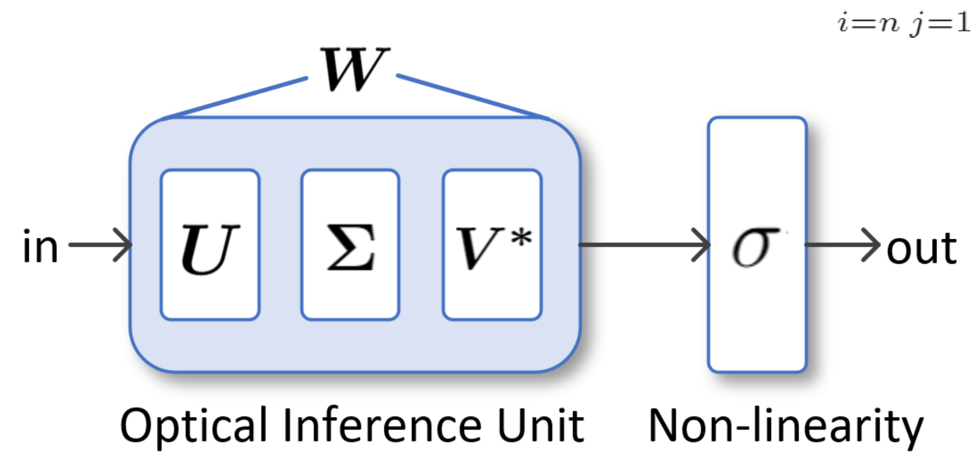


- $T\Sigma U$-based ONNs with MZIs and sparse tree

[ASPDAC'19, Zhao+]

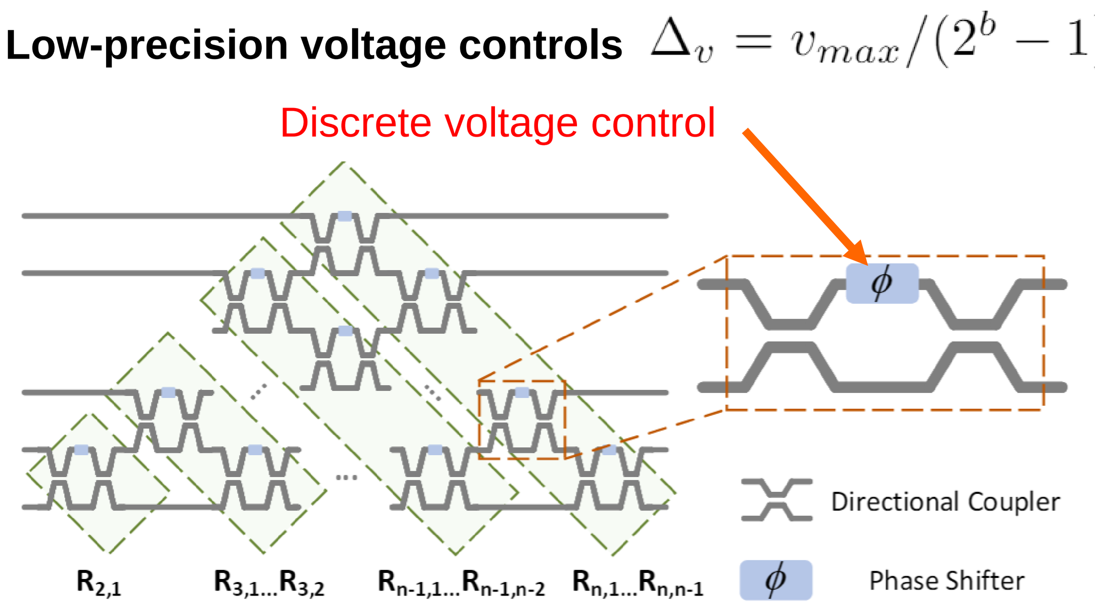
Principles of ONNs

- **Singular value decomposition (SVD)** $W = U\Sigma V^*$
- **Unitary group parametrization** $U(n) = D\prod_{i=n}^{2}\prod_{j=1}^{i-1} R_{ij}$

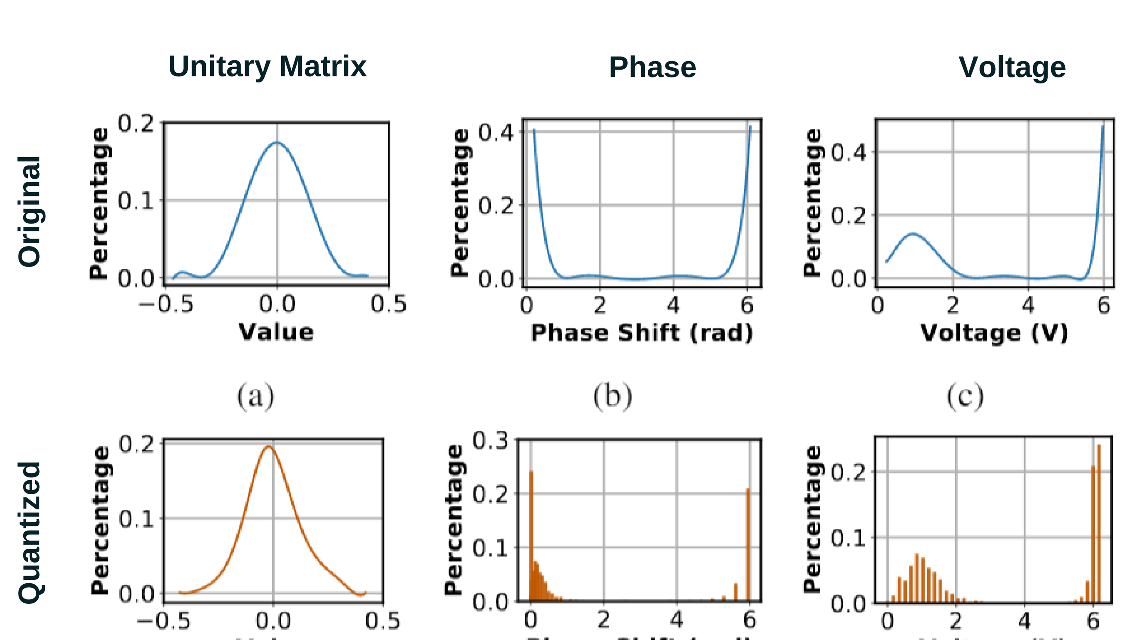


Non-ideality in ONNs: Low-Resolution Controls

- **Low-precision voltage controls** $\Delta_v = v_{max}/(2^b - 1)$



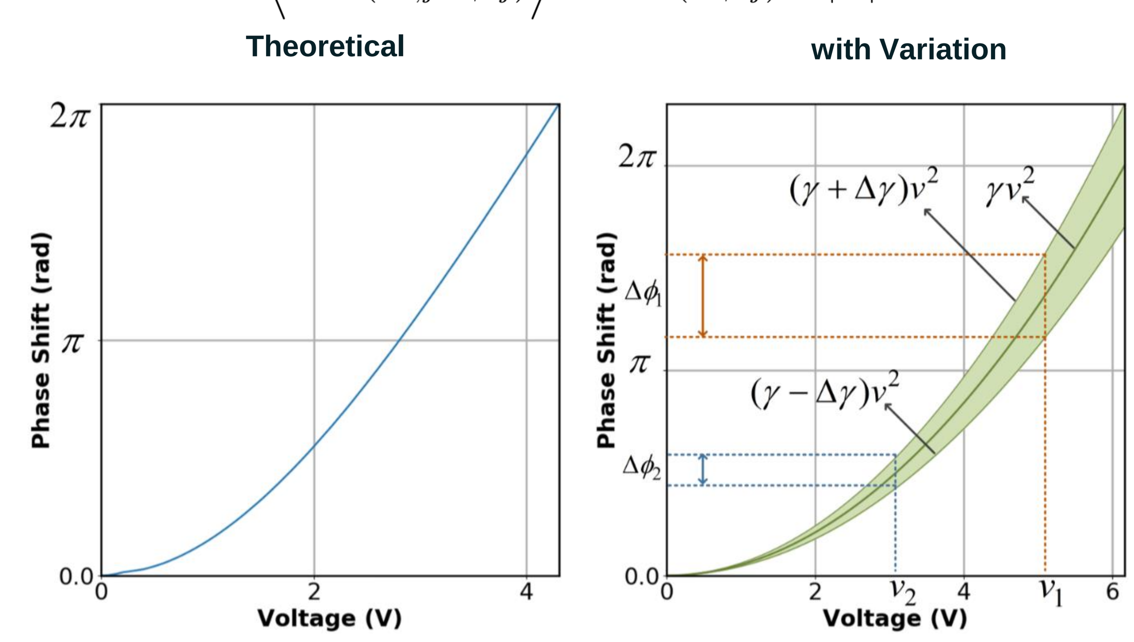
- **Limited phase encoding precision: quantization error**
- **Only** $\lfloor \frac{v_{2\pi}}{v_{max}} 2^b \rfloor$ **valid phases within [0, 2π]**



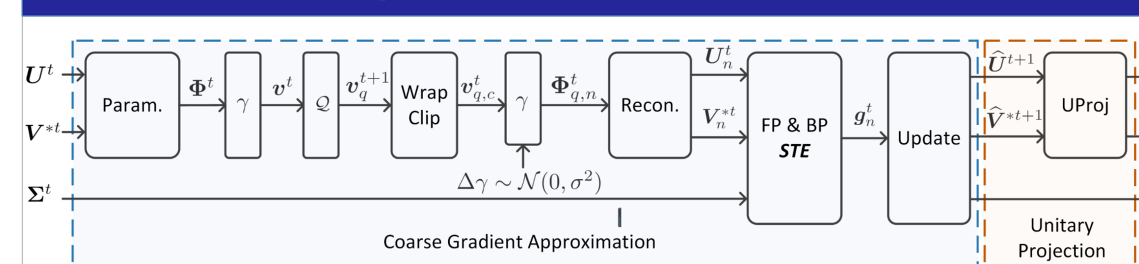
Non-ideality in ONNs: Device Variation

- **Gamma noise** $\Delta\gamma \sim \mathcal{N}(0, \sigma^2)$
  - Environmental changes
  - Manufacturing variations
  - Temperature changes
- **Non-ideal phase shifter response: weight error**

$$\langle \Delta W(\Sigma_{i,j}\Delta\phi_{ij}) \rangle = \Delta W(\Delta\phi_{ij}) \propto |\Phi|$$



Proposed Quantization Scheme



- **Coarse gradient approximation**
  - STE-based gradient propagation
- **Unitary projection**
  - Map U and V* to unitary planes
- **Blocking matrix multiplication**
  - Better scalability

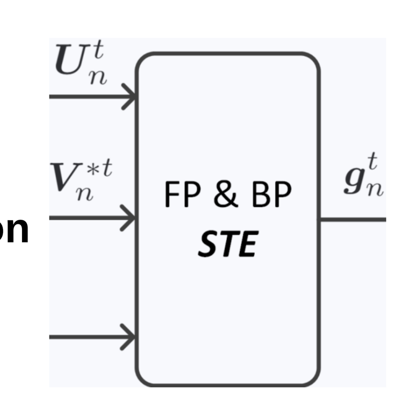
Coarse Gradient Approximation

- **Voltage quantization**

$$U_q^t = \mathcal{Q}_b(U^t)$$

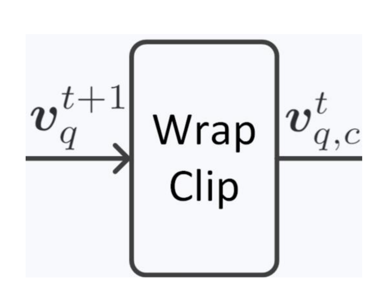
- **STE for efficient gradient propagation**

$$g_q^t = \frac{\partial L^t}{\partial U^t} = \frac{\partial L^t}{\partial U_q^t}$$



- **Wrap clipping of phases**
  - Reduce quantization error and noise sensitivity

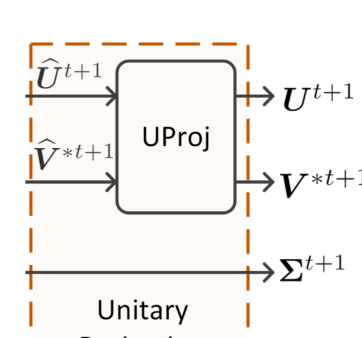
$$\texttt{WrapClip}(v_q) = \begin{cases} v_q, & \text{if } 0 \le v_q < v_{2\pi} \\ 0, & \text{if } v_q \ge v_{2\pi}. \end{cases}$$

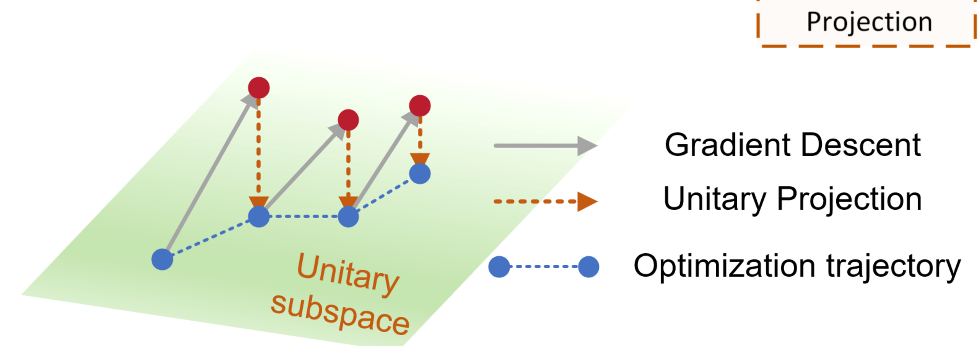


Unitary Projection

- **Satisfy unitary constraint**
- **SVD method minimizes projection error**

$$U = \texttt{UProj}(\hat{U}) \left\{ \begin{array}{l} PSQ^* = \texttt{SVD}(\hat{U}) \\ U = PQ^*. \end{array} \right.$$



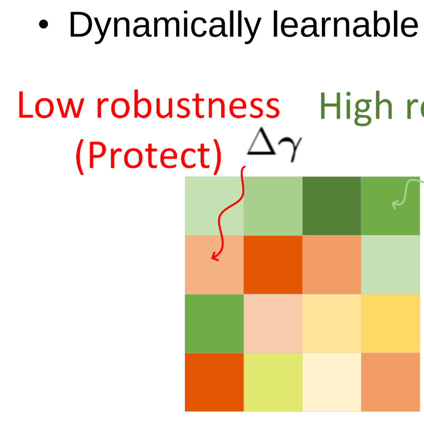


Noise-Aware Training Strategy

- Protective group Lasso regularization (PGL)
- Penalize sensitive weight blocks

$$\mathcal{L}_{PGL} = \sum_{l=1}^{L}\sum_{i=1}^{p^l}\sum_{j=1}^{q^l} P_{ij}^l \sqrt{1/\beta_{ij}^l}\, \|W_{ij}^l\|_2^2$$

- Dynamically learnable protective coefficient through EMA

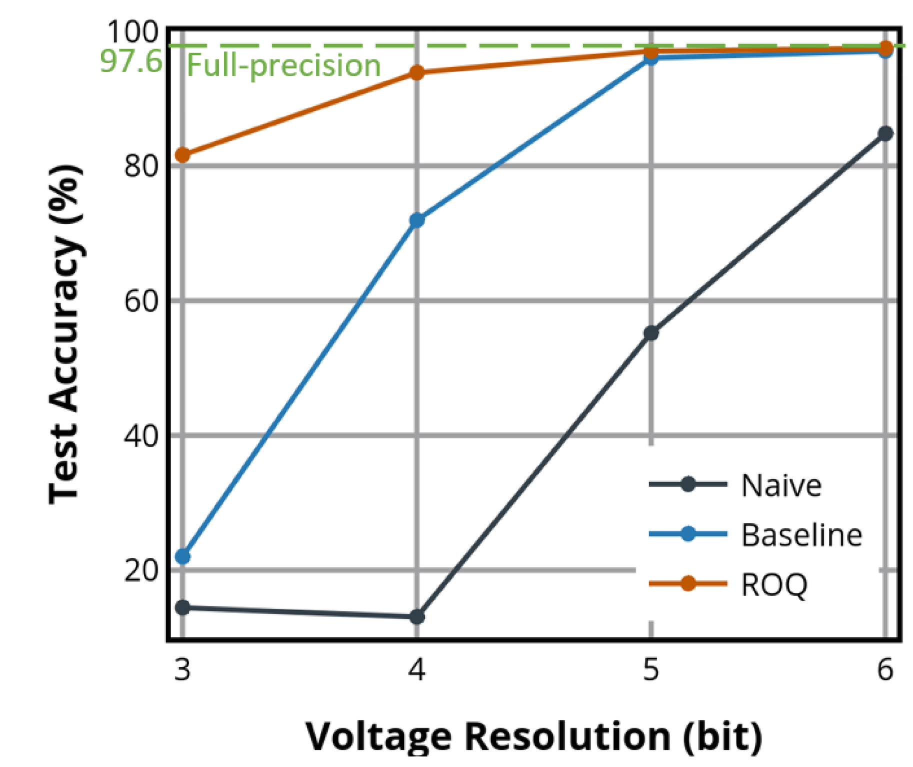


$$P_{ij}^l = \frac{d(W_{ij,q}^l, W_{ij,q,n}^l)}{\max_{i,j}(d(W_{ij,q}^l, W_{ij,q,n}^l))}$$

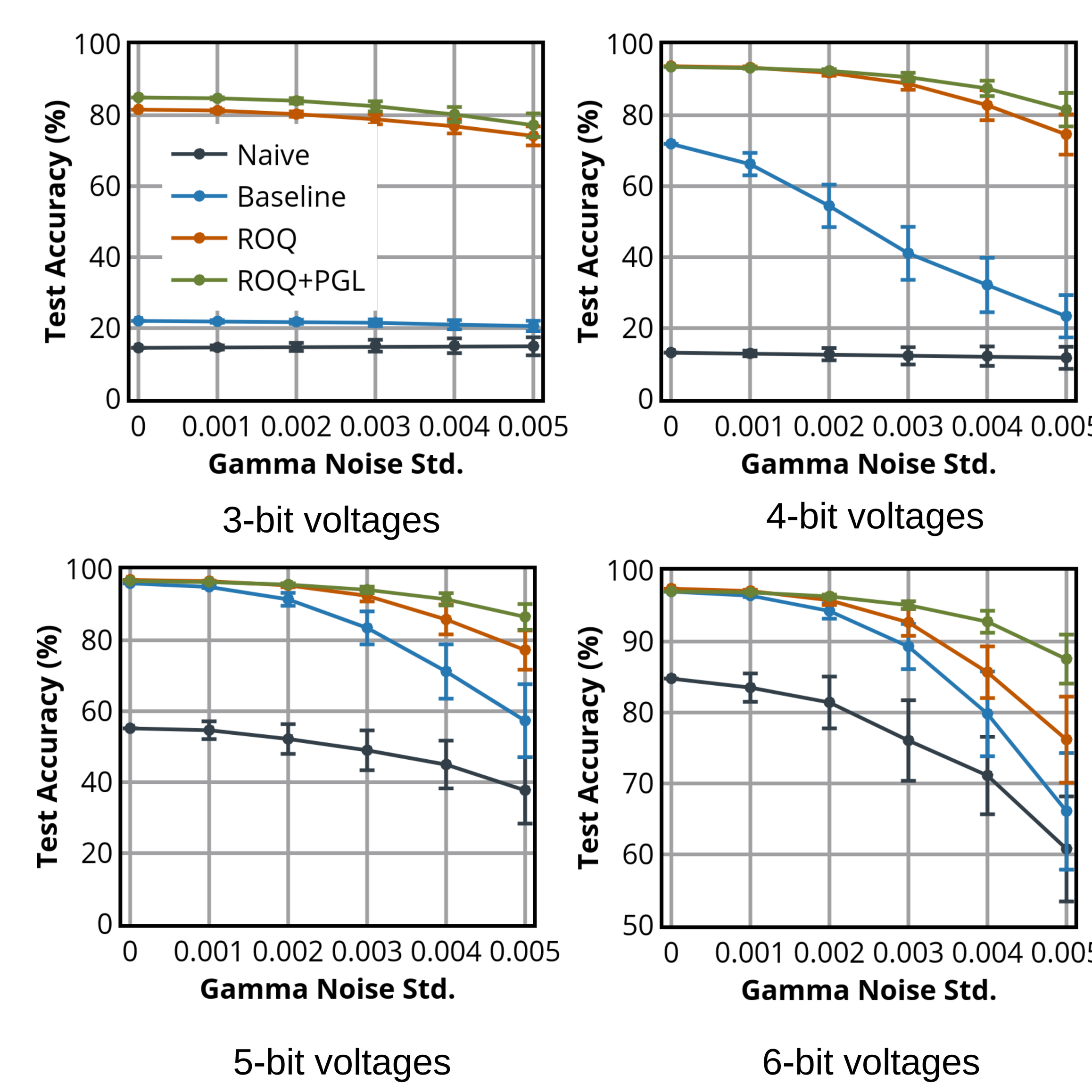
$$\hat{P}_{ij}^{l(t)} = \eta \hat{P}_{ij}^{l(t-1)} + (1-\eta)P_{ij}^{l(t)}$$

Experimental Results

- **Better accuracy under low-bit controls**
  - ONN config: 144-64(8)-64(8)-40(10)-10 on MNIST



- **Better noise robustness under 3~6-bit controls**
  - Gamma noise: std. 1e-3 ~ 5e-3



Contribution

Voltage-domain quantization scheme for ONNs

- **Traditional post-training quantization and iterative methods fail to train quantized ONNs**
- **~90% accuracy under 4-,5-,6-bit voltage controls**
- **>80% accuracy under 3-bit voltage control**

Noise-aware training strategy for ONNs

- **Protective Group Lasso regularization technique to boost noise-robustness of quantized ONNs**
- **>80% inference accuracy under 3-bit control and 5e-3 gamma noise, compared to ~20% for baseline method**
- **Lower accuracy variation under device-level noise**

Conclusion and Future Work

- Experimentally show that previous quantization methods perform poorly on ONN voltage quantization with device noise
- An end-to-end quantization scheme to enable low-precision voltage control of ONNs
- Protective group Lasso technique to boost noise-robustness of quantized ONNs
- Address other noise sources and apply to more ONN architectures