OPQ: Compressing Deep Neural Networks with One-shot Pruning-Quantization

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Presented by,
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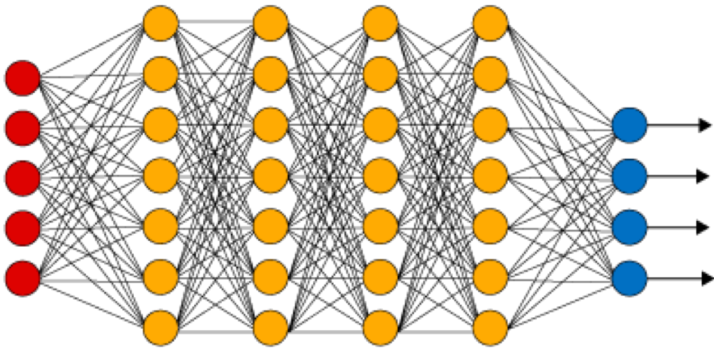
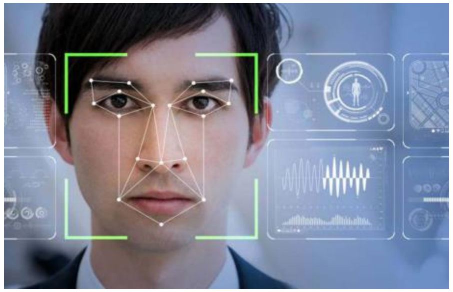
Outline

- Motivation
- Model Compression preliminary
- Unified Layer-wise Weight Pruning
- Unified Channel-wise Weight Quantization
- Experiments
- Conclusion

Introduction

- The success of modern deep neural networks (DNNs) is mainly dependent on the availability of advanced computing power and large data





Facial recognition

Smart healthcare

- However, its large model size and high computational operations, have impeded DNNs popularity, especially on mobile devices

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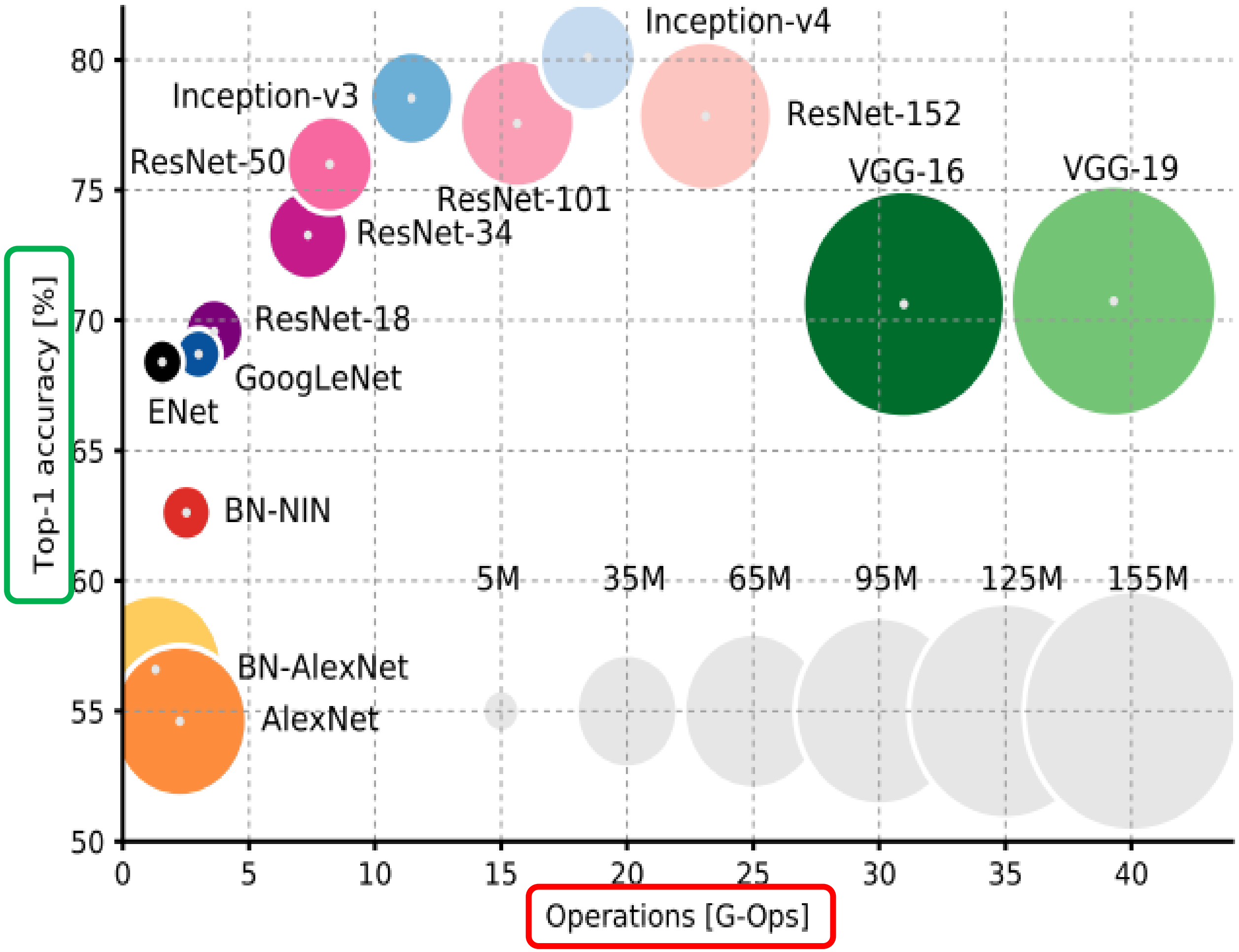
Motivation



Scaling up DNN size improves model accuracy.

Large model impedes training on resource-constrained devices!

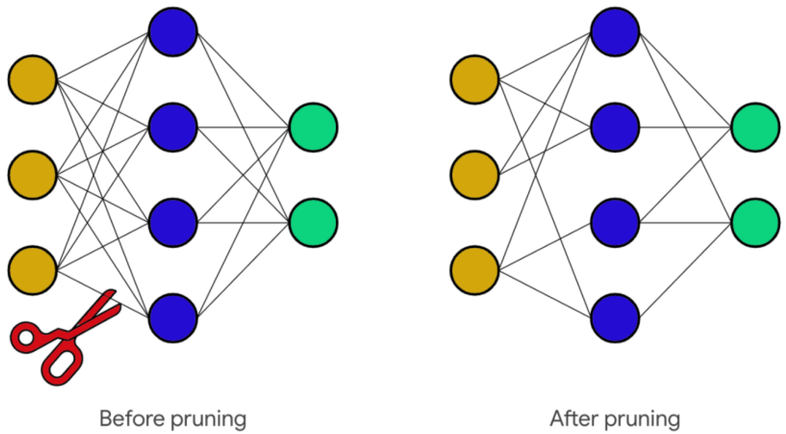
- ***Low memory resources***
- ***Expensive computation***
- ***Limited storage space***
- ***Increased latency at inference***

Source : A. Canziani, A. Paszke, and E. Culurciello. An analysis of deep neural network models for practical applications. In IEEE International Symposium on Circuits & Systems, 2016.

Preliminary - Model Compression

- Model compression methods: reduce the model size significantly

- Pruning:
  - Removes unimportant connections
  - Weights less than a salient threshold are set to zero



- Quantization:
  - Typically, weights : 32-bit floating point : precision not necessary
  - Reduces the number of bits required to represent a number
  - Reduces memory storage and computation costs

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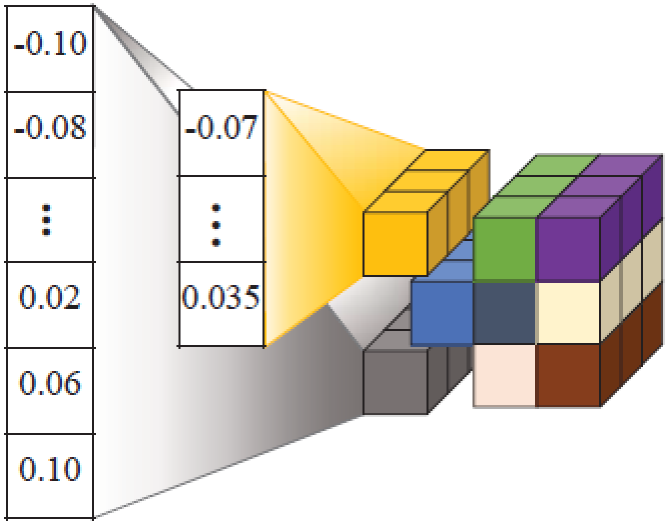
Challenges

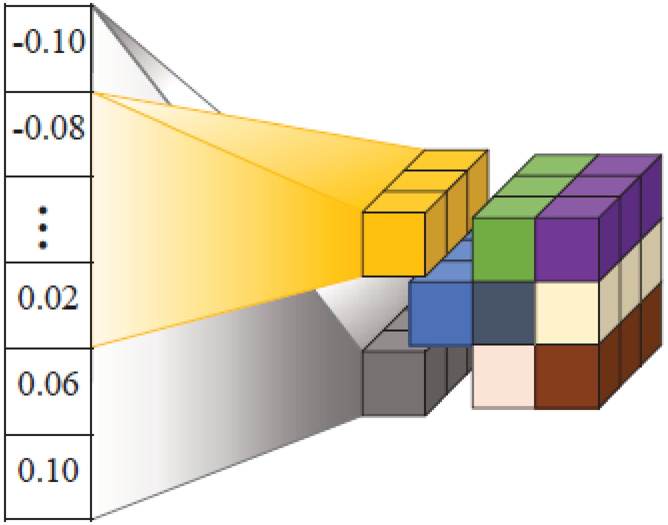
- Existing solutions are inefficient: iterative/manual fashion compression allocation + accuracy loss
- Each channel of a layer has its own channel-specific quantizer
- Expense of extra overhead introduced by channel-wise codebooks



- Pruning + quantization: almost impossible to manually tune the pruning ratios and quantization codebooks at fine-grained levels

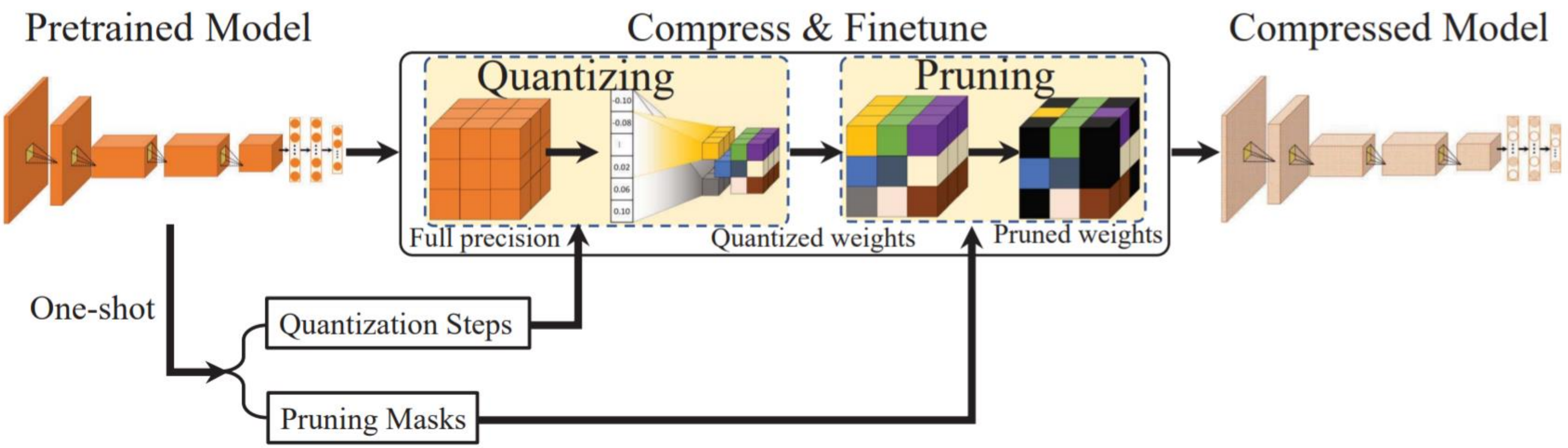
Strategy

- Proposed methods:
  - One-shot Pruning-Quantization (OPQ)
  - Unified channel-wise quantization



- Claim: Pre-trained model is sufficient for solving pruning and quantization simultaneously
- During finetuning, the compression module is fixed and only weight parameters are updated

Method pipeline



- Channels of each layer share the same quantizer (i.e., the same codebook)
- No additional computation burdens
- Given a pre-trained model, the pruning masks and quantization steps are analytically derived in one-shot
- Fixed while finetuning the compressed model.

Proposed method

- On a pre-trained model, the pruning-quantization is conducted on its weight parameters,

$$\boxed{\hat{\mathbf{W}} = \mathbf{M} \circ (\Delta \lfloor \frac{\mathbf{W}}{\Delta} \rceil)}$$

Pruning masks $\{\mathbf{M}_i\}_{i=1}^{L}$
Quantization steps $\{\Delta_i\}_i^L$

1: Compute the pruning masks $\{\mathbf{M}_i\}_{i=1}^{L}$ for all layers (see Section 3.2).
2: Calculate the qunatization steps $\{\Delta_i\}_i^L$ for all layer (see Section 3.3).
3: **for** $1, 2, \cdots, N_e$ **do**
4:     **repeat**
5:         Randomly sample a minbatch from the training set.
6:         Compress the weights using $\{\Delta_i\}_i^L$ and $\{\mathbf{M}_i\}_{i=1}^{L}$ for the model.
7:         Forward propagate with the pruned and quantized weights, and compute the cross entropy loss.
8:         Update the model weights with descending their stochastic gradient.
9:     **until** all samples selected
10: **end for**

Unified Layer-wise Weight Pruning

- General unified formulation to prune the weights W of all layers
- Find the pruning ratios of all layers $\{p_i\}_{i=1}^{L}$: percentage of weights with small magnitude,

$$p = \frac{1}{N}\sum_{i=1}^{L}\int_{-\beta_i}^{\beta_i} N_i f_i(x)dx = \frac{2}{N}\sum_{i=1}^{L}\int_{0}^{\beta_i} N_i f_i(x)dx. \quad (1)$$

symmetric range $[-\bar{\beta}_i, \beta_i]$: positive scalar value

- Pruning error,

$$\mathcal{L}_i^{\beta} = \sum_{j=1}^{N_i} (W_{ij})^2 \Big|_{|W_{ij}|\leqslant\beta_i} = 2\int_{0}^{\beta_i} N_i x^2 f_i(x)dx. \quad (2)$$

Unified Layer-wise Weight Pruning

- Pruning objective function,

$$\beta_1^*, \cdots, \beta_L^* = \underset{\beta_1, \beta_2, \cdots, \beta_L}{\arg\min} \frac{1}{N} \sum_{i=1}^{L} \mathcal{L}_i^{\beta} = \underset{\beta_1, \beta_2, \cdots, \beta_L}{\arg\min} \frac{2}{N} \sum_{i=1}^{L} \int_0^{\beta_i} N_i x^2 f_i(x) dx.$$

- For a given objective pruning rate p*,

$$\mathcal{L}(\beta_1, \cdots, \beta_L, \lambda) = \sum_{i=1}^{L} \frac{2}{N} \int_0^{\beta_i} N_i x^2 f_i(x) dx - \lambda \left(\frac{2}{N} \sum_{i=1}^{L} \int_0^{\beta_i} N_i f_i(x) dx - p^* \right)$$

- Since $f_i(x)$ could be a Laplace probability density function

$$\boxed{\frac{\partial \mathcal{L}(\beta_1, \cdots, \beta_L, \lambda)}{\partial \lambda} \approx \frac{1}{N} \sum_{i=1}^{L} N_i \left(1 - e^{-\frac{\sqrt{\lambda}}{\tau_i}} \right) - p^*}$$

- Levenberg-Marquardt algorithm, Newton-Raphson methods are used
- Finally derive binary mask

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Unified Channel-wise Weight Quantization

- Number of quantization bins required to store the unpruned weights of the channel,

$$\boxed{K_{ij} = \left\lfloor \frac{2\alpha_{ij}}{\Delta_i} \right\rceil}$$

Range $[-\alpha_{ij}, \alpha_{ij}]$: positive real value

- Per layer and the whole model,

$$\boxed{K_i = \frac{1}{\bar{N}_i} \sum_{j=1}^{C_i} \bar{N}_{ij} K_{ij},} \qquad \boxed{\frac{1}{\bar{N}} \sum_{i=1}^{L} K_i N_i \int_{\beta_i}^{+\infty} f_i(x) dx = \frac{1}{\bar{N}} \sum_{i=1}^{L} \sum_{j=1}^{C_i} \bar{N}_{ij} K_{ij} = 2^B}$$

- Common quantization function,

$$\boxed{Q_i(x) = \mathrm{sgn}(x) \Delta_i \left\lfloor \frac{|x|}{\Delta_i} \right\rceil}$$

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Unified Channel-wise Weight Quantization

- Mean-square errors caused by quantization,

$$\boxed{\mathcal{L}_q = 2\sum_{i=1}^{L}\frac{1}{\bar{N}_i}\int_{\beta_i}^{+\infty} N_i f_i(x)(x - Q_i(x))^2 dx \approx \sum_{i=1}^{L}\frac{\Delta_i^2}{12}}$$

Solve using lagrangian,

$$\boxed{\Delta_i = \frac{1}{2^{B-1}\bar{N}}\sum_{i=1}^{L}\sum_{j=1}^{C_i}\bar{N}_{ij}\alpha_{ij}}$$

$$\boxed{\lambda = \left(\frac{1}{2^{B-1}\bar{N}}\sum_{i=1}^{L}\sqrt[3]{\frac{\bar{N}}{12}}\frac{\sum_{j=1}^{C_i}\bar{N}_{ij}\alpha_{ij}}{\sqrt[3]{\sum_{j=1}^{C_i}\bar{N}_{ij}\alpha_{ij}}}\right)^3}$$

- Combining the above equations, we obtain the quantization quotas for all layers, which can be used to quantize the given DNN model

Experiments

- Models
  - AlexNet, VGG-16, ResNet-50, MobileNet-V1
- Dataset – ImageNet
- Baselines
  - **Pruning** : Data-Free Pruning (Srinivas and Babu 2015),
  - Adaptive Fastfood 32 (Yang et al. 2015),
  - Less Is More (Zhou, Alvarez, and Porikli 2016),
  - Dynamic Network Surgery (Guo, Yao, and Chen 2016),
  - Circulant CNN (Cheng et al. 2015),
  - and Constraint-Aware (Chen et al. 2018))
  - **Quantization** : Q-CNN (Wu et al. 2016),
  - Binary-Weight- Networks (Rastegari et al. 2016),
  - and ReNorm (He and Cheng 2018))
  - **pruning-quantization methods:** Deep Compression (Han, Mao, and Dally 2016), CLIP-Q (Tung and Mori 2020), and ANNC (Yang et al. 2020a)

Experiments

Method	Top-1 (%)	Top-5 (%)	Prune Rate (%)	Bit	Rate
Data-Free Pruning (Srinivas and Babu 2015)	55.60 (2.24↓)	-	36.24	32	1.57×
Adaptive Fastfood 32 (Yang et al. 2015)	**58.10** (0.69↑)	-	44.12	32	1.79×
Less Is More (Zhou, Alvarez, and Porikli 2016)	53.86 (0.57↓)	-	76.76	32	4.30×
Dynamic Network Surgery (Guo, Yao, and Chen 2016)	56.91 (0.3↑)	80.01 (-)	94.3	32	17.54×
Circulant CNN (Cheng et al. 2015)	56.8 (0.4↓)	**82.2** (0.7↓)	95.45	32	18.38×
Constraint-Aware (Chen et al. 2018)	54.84 (2.57↓)	-	**95.13**	32	20.53×
Q-CNN (Wu et al. 2016)	56.31 (0.99↓)	79.70 (0.60↓)	-	1.57	20.26×
Binary-Weight-Networks (Rastegari et al. 2016)	56.8 (0.2↑)	79.4 (0.8↓)	-	**1**	32×
Deep Compression (Han, Mao, and Dally 2016)	57.22 (0.00↑)	80.30 (0.03↑)	89	5.4	6.66×
CLIP-Q (Tung and Mori 2020)	57.9 (0.7↑)	-	91.96	3.34	119.09×
ANNC (Yang et al. 2020a)	57.52 (**1.00**↑)	80.22 (0.03↑)	92.6	3.7	118×
Ours	57.09 (0.46↑)	80.25 (**1.20**↑)	92.30	2.99	**138.96**×

Table 1: AlexNet on ImageNet.

Method	Top-1 (%)	Top-5 (%)	Prune Rate (%)	Bit	Rate
ThiNet-GAP (Luo, Wu, and Lin 2017)	67.34 (1.0↓)	87.92 (0.52↓)	94.00	32	16.63×
Q-CNN (Wu et al. 2016)	68.11 (3.04↓)	88.89 (1.06↓)	-	**1.35**	23.68×
Deep Compression (Han, Mao, and Dally 2016)	68.83 (0.33↑)	89.09 (**0.41**↑)	92.5	6.4	66.67×
CLIP-Q (Tung and Mori 2020)	69.2 (**0.7**↑)	-	94.20	3.06	180.47×
Ours	**71.39** (0.24↓)	**90.28** (0.09↓)	**94.41**	2.92	**195.87**×

Table 2: VGG-16 on ImageNet.

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Experiments

Method	Top-1 (%)	Top-5 (%)	Prune Rate (%)	Bit	Rate
To Prune or Not To Prune (Zhu and Gupta 2017)	69.5 (1.1↓)	89.5 (0.0↑)	50	32	2×
Deep Compression (Han, Mao, and Dally 2016)	65.93 (4.97↓)	86.85 (3.05↓)	-	3	10.67×
ReNorm (He and Cheng 2018)	65.93 (9.75↓)	83.48 (6.37↓)	-	4	8×
HAQ (Wang et al. 2019)	67.66 (3.24↓)	88.21 (1.69↓)	-	3	10.67×
CLIP-Q (Tung and Mori 2020)	70.3 (0.0↑)	-	47.36	4.61	13.19×
ANNC (Yang et al. 2020a)	69.71 (1.19↓)	89.14 (0.76↓)	-	3	10.67×
ANNC (Yang et al. 2020a)	66.49 (4.41↓)	87.29 (2.61↓)	58	**2.8**	26.7×
Ours	**70.83 (0.55↑)**	**89.70 (0.27↑)**	57.78	3.26	23.26×
Ours	70.24 (0.04↓)	89.30 (0.13↓)	**67.66**	3.08	**32.15**×

Table 3: MobileNet-V1 on ImageNet.

Method	Top-1 (%)	Top-5 (%)	Prune Rate (%)	Bit	Rate
ThiNet (Luo, Wu, and Lin 2017)	71.01 (1.87↓)	90.02 (1.12↓)	51.76	32	2.07×
Deep Compression (Han, Mao, and Dally 2016)	76.15 (0.00↑)	92.88 (0.02↑)	-	4	8×
HAQ (Wang et al. 2019)	76.14 (0.01↓)	92.89 (0.03↑)	-	4	8×
ACIQ (Banner, Nahshan, and Soudry 2019)	75.3 (0.8↓)	-	-	4	8×
CLIP-Q (Tung and Mori 2020)	73.7 (**0.6**↑)	-	69.38	3.28	31.81×
Ours	**76.41** (0.40↑)	**93.04 (0.11↑)**	**74.14**	**3.25**	**38.03**×

Table 4: ResNet-50 on ImageNet.

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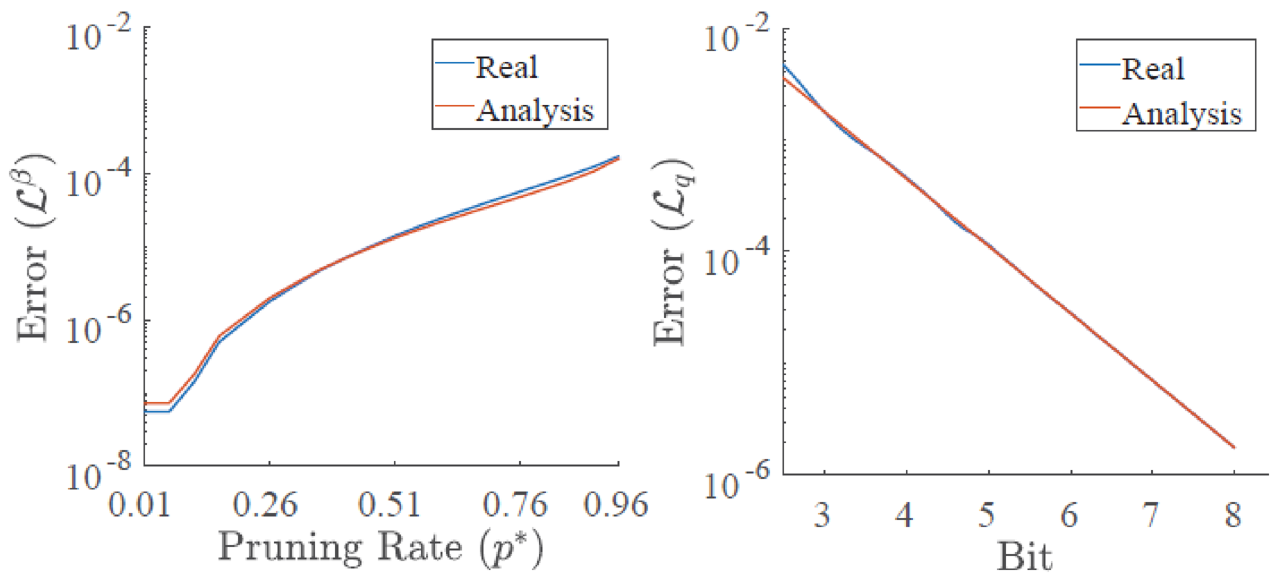
Error Analysis

- Pruning: Laplace probability density function approximates the real pruning error well, demonstrating the validity of the equation
- Quantization: approximation error is in a good agreement with the real quantization error



(a) Pruning Error Analysis. (b) Quantization Error Analysis.

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Conclusion

- The paper proposed a novel One-shot Pruning-Quantization method (OPQ) to compress DNN models
- Their method has addressed two challenging problems in network compression.
  - First, different from the prior art, OPQ is a one-shot compression method without manual tuning or iterative optimization of the compression strategy
  - Second, their unified channel-wise pruning to enforce all channels of each layer to share a common codebook, avoids the overheads brought by the traditional channel-wise quantization
- Experiments show that their method achieves superior results comparing to the state-of-the-art.

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Discussion

- For future work, we will explore how to further compress DNN model
- Implement their method with custom hardware architecture
- Validate the inference efficiency of the compressed models on practical hardware platforms.
- Potential negative impact: the compression bias caused by OPQ because of unusual weight distribution, too lower objective compression rate, etc

THANK YOU

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