# LQ-Nets: Learned Quantization for Highly Accurate and Compact Deep Neural Networks (*Supplementary Material*)

## 1 Statistics of Weights and Activations

In the main paper we presented the statistics of weights and activations in the ResNet-20 model quantized with "2/2" bits. Here we show the cases with "3/3" bit-widths in Fig. I.

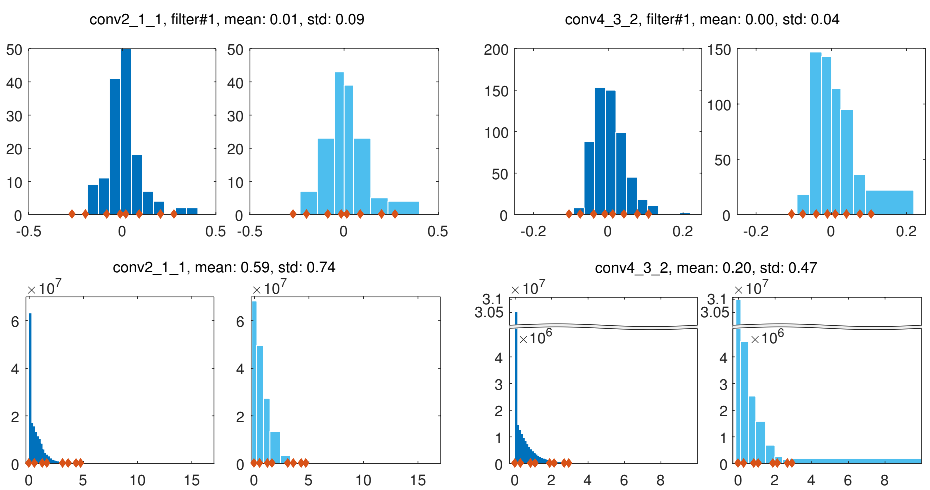


**Fig. I:** Statistics of the weights (top row) and activations (bottom row) before (i.e., the floating-point values) and after quantization. The ResNet-20 model with "3/3" quantization is used. The orange diamonds indicate the eight quantization levels of our learned quantizers. Note that in the left figures for the floating-point values the histogram bins are of equal step size, whereas in the right figures each of the four bins contains all the values quantized to its corresponding quantization levels.

## 2 Detailed Hyper-Parameter and Other Setups

We presented here the detailed hyper-parameters and other training setups that are omitted in the main paper due to space limitation.

### 2.1 CIFAR-10 Experiments

**Data augmentation:** Following [4, 2], in the training stage we pad 4 pixels on each side of the original 32×32 images, and randomly crop a 32×32 sample or its horizontal flip. The original images are used at test time.

**Hyper-parameters:** For all the experiments on CIFAR-10, we train the models for up to 200 epochs and use a momentum of 0.9. For the ResNet-20 model, the learning rate starts at 0.1 and is divided by 10 at 82 and 123 epochs. Weight decay of $1e-4$ and batch size of 128 are adopted following the original paper. For VGG-Small, the learning rate starts at 0.02 and is divided by 10 at 80 and 160 epochs. Following [1], we set weight decay to $5e-4$ and batch size to 100.

### 2.2 ImageNet Experiments

**Data augmentation:** Our data augmentation strategy mostly follows [1]. During training, we first resize the shorter side of the images to 256, and then randomly sample 224×224 (227×227 for AlexNet) image crops with horizontal flipping applied at random. At test time, a single, centered crop of size 224×224 (227×227 for AlexNet) is used for each image. When training networks with bit-widths larger than "1/2", we follow the augmentation strategy of the ResNet Torch implementation[1]. Specifically, we use the scale and aspect ratio augmentation from [5] and color augmentation proposed in [3].

**Hyper-parameters:** For all the experiments on ImageNet, following [2] we train the models for up to 120 epochs with a momentum of 0.9. For all the experiments with bit-widths larger than "1/2", the batch size is 256 and the weight decay is $1e-4$. The learning rate starts at 0.1 and is divided by 10 at 30, 60, 85, 95, 105 epochs.

When comparing against HWGQ [1] on ResNet, AlexNet, VGG-Variant and GoogLeNet with bit-widths of "1/2", we use the same hyper-parameters in HWGQ's implementation. Specifically, the learning rate starts at 0.1 for ResNet and GoogLeNet, 0.01 for VGG-Variant, and 0.02 for AlexNet, respectively. Polynomial learning rate annealing with power of 1 is adopted instead of the multi-step annealing. The total training epoch is set to 64 for all experiments. The batch size is 128 for VGG-Variant and 256 for others. The weight decay is $5e-4$ for AlexNet and VGG-Variant, and $5e-5$ for ResNet and GoogLeNet.

## References


1. Cai, Z., He, X., Sun, J., Vasconcelos, N.: Deep learning with low precision by half-wave gaussian quantization. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 5918–5926 (2017)


[1] https://github.com/facebook/fb.resnet.torch (accessed July 10, 2018)

2. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 770–778 (2016)
3. Howard, A.G.: Some improvements on deep convolutional neural network based image classification. arXiv:1312.5402 (2013)
4. Lee, C.Y., Xie, S., Gallagher, P., Zhang, Z., Tu, Z.: Deeply-supervised nets. In: Artificial Intelligence and Statistics (AISTATS). pp. 562–570 (2015)
5. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., Hill, C., Arbor, A.: Going deeper with convolutions. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 1–9 (2015)