In this paper, we propose a Dynamic Network Quantization (DNQ) framework. Unlike most existing quantization methods that use a universal quantization bit-width for the whole network, we utilize policy gradient [1] to train an agent to learn the bit-width of each layer by the bit-width controller.

Our bit-width controller in this work is based on reinforcement learning for training an agent to maximize the cumulative reward. This problem is solved by training a policy network $M_\theta$, the input sequence is the embedding of the network and the output sequence $B_L = (b_1, \ldots, b_l, \ldots, b_L)$ is the bit-widths of the network, where $b_l$ is the bit-width of the $l$th layer. In time step $l$, the state $s$ is the current produced bit-width sequence $(b_1, \ldots, b_{l-1})$. The action $a_l$ we choose in time step $l$ indicates the bit-width used to quantize the layer, where $a_l \in (2, 3, \ldots, 8)$. Thus, the reward $R$ is defined as $Acc + \lambda r$, where $Acc$ is the accuracy of the quantized network without fine-tuning and $r$ is the compression ratio. We should not only consider the fitness of previous layers’ bit-widths but also the future outcome. Therefore, to evaluate the action $a_t$ in time step $t$, we apply Monte Carlo search to sample the next $L-t$ bit-widths. We average the $N$ times sampling results to reduce the variance:

$$R^{M_\theta}(s_t = B_{t-1}, a_t = b_t) = \frac{1}{N} \sum_{n=1}^{N} R_n(B_L), \quad B_L = MC(B_t; N), \quad (1)$$

where $MC(:)$ is the Monte Carlo sampling function. We train our policy networks by policy gradient [1].

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References

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