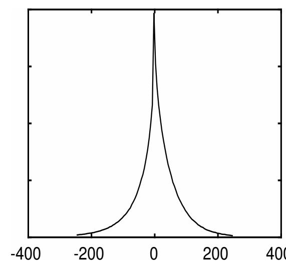
Enhanced Bayesian Compression via Deep Reinforcement Learning

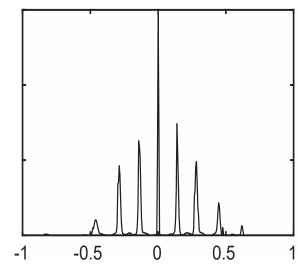
Xin Yuan[1,2,3,*], Liangliang Ren[1,2,3,*], Jiwen Lu[1,2,3,†], Jie Zhou[1,2,3]
[1]Department of Automation, Tsinghua University
[2]State Key Lab of Intelligent Technologies and Systems, Tsinghua University
[3]Beijing National Research Center for Information Science and Technology
{yuanx16, renll16}@mails.tsinghua.edu.cn; {lujiwen, jzhou}@tsinghua.edu.cn

Abstract

In this paper, we propose a Enhanced Bayesian Compression method to flexibly compress the deep networks via reinforcement learning. Unlike existing Bayesian compression methods which can not explicitly enforce quantization weights during training, our method learns flexible codebooks in each layer for an optimal network quantization. To dynamically adjust the state of codebooks, we employ an Actor-Critic network to collaborate with the original deep network. Unlike most existing network quantization methods, our EBC doesn't require re-training procedures after the quantization. Experimental results show that our method obtains low-bit precision with acceptable accuracy drop on MNIST, CIFAR and ImageNet.



(a) original model



(b) EBC model

Figure 1. The main idea of the proposed Enhanced Bayesian Compression (EBC) method. EBC aims to learn flexible codebooks in each layer for an optimal network quantization. The original model weights in (a) have a new distribution as shown in (b) after our EBC training, which can be directly quantized to the codebook values with a restrained quantization error impact.

1. Introduction

Deep neural networks (DNNs) have achieved dramatic accuracy improvements in a variety of machine learning tasks such as image classification [35, 52], speech recognition [14] and natural language processing [53]. Recent research progress further shows that the performance of DNNs on these tasks can benefit from increasing network depth and width [19, 24]. Despite the success, large size DNNs are difficult to be deployed on resource-limited devices such as mobiles and embedded systems because of the high cost of computations and hardware resources. To address this, some deep network compression methods have been proposed to reduce the parameter redundancy and the effective fixed point precision in recent years.

Most existing networks compression methods focus on pruning and quantization. Network pruning [17, 16] aim to remove redundant weight parameters, neurons or filters permanently from neural network. For example, [18, 16] pruned unnecessary connections according to the absolute weight value, which may fail to determine the weights that indeed contribute much to the overall computation. Network quantization [18, 59, 28] has been proposed for the reduction of the bit precision of weights, activations or even gradients. For example, [18] employed a conventional quantization method for network quantization. However, these methods suffer from accuracy losses because of the quantization errors and rely on a highly computational retraining after quantization. There are some other works involving CNNs efficiency improvements, which have been studied in previous works [27, 22, 58, 23]. For example, [25, 49] are proposed using binary weights and activations, which benefit from the small storage and efficient computation by bit-counting operation. Another popular variant is depth-wise separable convolution [50], which applies a separate convolutional kernel to each channel, followed by a point-wise convolution over all channels [10, 22, 58]. Most of these methods focus on finding an efficient alternative for standard spatial convolutions hence learning a compressed network from scratch.

More recently, some compression methods [42, 55, 45, 46] have been proposed to prune the network and reduce

*Indicates equal contribution
†Corresponding author.

bit precision for the weights from a Bayesian perspective. These Bayesian methods take the advantages of variational Bayesian approximation which automatically reduce parameter redundancy by penalizing the complex models, where variational posterior uncertainty is used to determine which bits are significant and derive the optimal efficient bit precision. Despite the Bayesian bonus, such methods fail to explicitly enforce the model weights quantized based on a low-bit codebook during training which usually can not achieve a high quantization compression ratio.

In this paper, we propose a Enhanced Bayesian Compression (EBC) method to flexibly compress the deep network via reinforcement learning. We assign parameters to the codebook values the following the criterions: (1) weights are assigned to the quantized values controlled by agents with the highest probability. (2) the input and output activations are highly correlated under the distribution estimated by agents. As shown in Figure 1, we enforce the network to achieve a flexible codebook with a low variance after EBC training. Instead of EM which requires all the data as input and cannot derive the probability of feature maps from the GMM model, we model the update of weights in a deep neural network as a Markov decision process and use the learnable actor-critic network to collaborate with the deep neural network to dynamically adjust codebooks. Been different from other GMM-based Bayesian compression methods like SWS, which only learns the prior from the distribution of parameters and calculate the gradients of the classifier while ignoring the input data (or features), our method uses the RL to collaborate with both the original network parameters and feature maps to adjust the number and parameters of the weights' distribution. For example, in the case of sparse inputs, SWS is hard to train because the gradients, as well as the initial parameters are non-zero values. Our method doesn't require re-training steps after quantization. Experimental results show that our method obtains low-bit precision with acceptable accuracy losses on three widely used datasets (MNIST, CIFAR-10, ImageNet) using different deep networks.

2. Related Work

Deep Network Compression: Deep network compression is of great interest in recent years to reduce computational cost and memory requirements to make deep neural networks portable. For example, Gong et al. [13] addressed the storage problem of AlexNet with vector quantization techniques. Han et al. [17] presented a deep compression method which combines the pruning [18], quantization and Huffman coding for better compression. Efficiency improvements in less computationally-intensive convolutions have been studied in previous works [27, 22, 58, 23, 25, 49]. The recently proposed BinaryConnect [11] compresses DNNs by a factor of 32 using binary weights and activations, which benefit from the small storage and efficient computation by bitcounting operation, without a noticeable accuracy loss for small datasets. After that, a series of methods [25, 49, 26] have been proposed to train CNNs with low-precision weights and low-precision activations. LBP-CNN [29] proposes a separable convolution to freeze spatial convolutions and learn only point-wise convolutions. Another widely applied example is the depth-wise separable convolution which applies a separate convolutional kernel to each channel, followed by a point-wise convolution over all channels. ResNext [19], MobileNet [22] and Xception [10] adopt group convolutions and depth-wise separable convolutions as alternatives to standard spatial convolutions. ShuffleNet [58] integrates depth-wise convolutions, point-wise group convolutions, and channel-wise shuffling for further acceleration. In addition to find efficient alternatives, dynamic network executions have been studied in previous works [8, 39, 47]. Some conditional computation methods [1, 5, 6, 41] activate part of a network under a learned policy.

Pruning and reducing bit precision for the weights from a Bayesian perspective achieves more attention in recent years, which can keep high accuracy after compression. Sparse VD [45] leads to extremely sparse solutions both in fully-connected and convolutional layers. Bayesian Compression [42] is proposed to prune whole neurons or filters via group-sparsity constraints. Structured Bayesian Pruning [46] extends Sparse VD, which prunes whole neurons or filters under the group-sparsity constraints. Soft weight sharing (SWS) [55] is a Bayesian method quantizing and pruning networks, which involves a Gaussian mixture model prior with automatic collapse of unnecessary mixture components. SWS learns the prior from the data while our method explicitly uses RL to collaborate with the original network for a more flexible codebook learning. Most Bayesian Compression methods cannot explicitly enforce quantizing on a low-bit codebook during training, which usually need a high bit precision.

Reinforcement Learning: Reinforcement learning (RL) [43, 44, 15, 56, 51, 2, 57, 9, 48, 33] has gained a significant success in various machine learning applications in recent years. For example, Mnih *et al* [43, 44] proposed a deep reinforcement learning model to learn control policies directly from high-dimensional sensory, and achieved better performance than human beings in several atari games. Cao et al. [9] proposed an attention-aware face hallucination framework with deep reinforcement learning to sequentially discover attended patches and perform the facial part enhancement by fully exploiting the global interdependency of the image. Kong et al. [33] presented a collaborative multi-agent deep reinforcement learning method to localize objects jointly than single agent detection. Liang et al. [40] proposed a deep variation-structured reinforcement learning

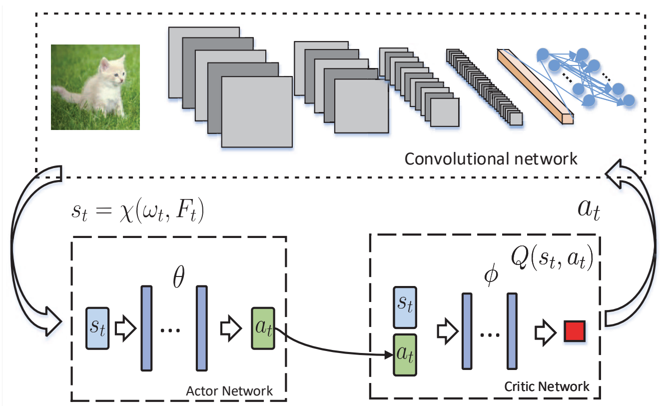


Figure 2. The framework of our proposed EBC approach, in which the backbone CNN network and the Actor-Critic network collaborates to learns flexible codebooks. In each layer of the backbone network, the actor network get state value and outputs an action which is evaluated by the critic network for updating the codebook.

framework to detect visual relationship and attributes with a directed semantic action graph.

Recent works on searching models with reinforcement learning greatly improve the performance of neural networks. NAS [61] aims to search the transferable network blocks whose performance surpasses many hand-crafted architectures. N2N [3] integrated reinforcement learning into channel selection. AMC [20] leveraged reinforcement learning for deep compression policy, with higher compression ratio while preserving the accuracy, which outperforms conventional rule-based compression policy. The concepts of state, action, rewards and transitions in RL also motivate us to leverage ideas from RL for Bayesian Compression. Compared with previous works, EBC optimizes for both accuracy and low-bit precision without any further re-training steps or extra system computational overloads.

3. Approach

In this section, we first describe the deep network compression framework from a Bayesian perspective. Then we propose our Deep Reinforcement Learning for Bayesian compression method. We map the problem of Bayesian compression problem onto the policy optimization problem via reinforcement learning. At last we introduce actor-critic network to collaborate with original network and optimize the EBC method for flexibly compression.

3.1. Bayesian Compression

Bayesian compression aims to prune deep networks and reduce bit precision for the weights while keeping high accuracy. The Bayesian methods [42, 55, 45, 46] search for the optimal model structure and determine required bit-precision per layer via uncertain posteriors over the parameters from a Bayesian perspective. In variational inference the evidence lower bound (ELBO) $\mathcal{L}^{ELBO} = -(\mathcal{L}^E + \mathcal{L}^C)$ is maximized for an optimal trade-off between short description length of the data and the model. According to the Minimum description length (MDL) principle, a model is optimal if it can minimize the combined cost of the description of model complexity ($\mathcal{L}^C$) and the misfit between the model and the data ($\mathcal{L}^E$). Bayesian methods investigate the equivalence of variational inference and the MDL principle based on the fundamental theorem in information theory.

Suppose we have a dataset $\mathcal{D}$ with N pairs of objects $(x_n, y_n)_{n=1}^N$. Let $p(\mathcal{D}|w) = \prod_{i=1}^N p(\boldsymbol{y}_i|\boldsymbol{x}_i, \boldsymbol{w})$ be a parameterized model that predicts outputs y_i, given inputs $\boldsymbol{x}_i$ and parameters $\boldsymbol{w}$ about which we usually have some prior knowledge $p(\boldsymbol{w})$. In Bayesian learning, we are interested in the posterior $p(\boldsymbol{w}|\mathcal{D}) = p(\mathcal{D}|\boldsymbol{w})p(\boldsymbol{w})/p(\mathcal{D})$, which is intractable for many models. Variational Inference is exploited to approximate the posterior distribution $p(\boldsymbol{w}|D)$ by a parametric distribution $q_\phi(\boldsymbol{w})$. Variational parameters ϕ are optimized by minimizing the Kullback-Leibler divergence, which denotes as $D_{KL}(q_\phi(\boldsymbol{w})||p(\boldsymbol{w}|D))$. Minimizing this KL divergence can be approximately performed by maximizing the aforementioned ELBO, which is also called "negative variational free energy" [31]:

$$\mathcal{L}(\phi) = \mathcal{L}_D(\phi) - D_{KL}(q_\phi(\boldsymbol{w})||p(\boldsymbol{w})) \tag{1}$$

$$\mathcal{L}_D(\phi) = \sum_{n=1}^{N} E_{q_\phi(\boldsymbol{w})}[\log p(y_n|x_n, w)] \tag{2}$$

where the variational lower bound in (1) and its gradients can not be computed. Some existing methods [45, 42] use the *Reparameterization Trick* to obtain an unbiased, differentiable, minibatch-based Monte Carlo estimator of the expected log likelihood:

$$\mathcal{L}_D^{SGVB}(\phi) = \frac{N}{M}\sum_{m=1}^{M} logp(\tilde{y_m}|\tilde{x_m}, f(\phi, \epsilon_m)) \tag{3}$$

Unlike previous works which use the *Reparameterization Trick* [7] to reduce variance of the stochastic ELBO gradient estimator, we reformulate the intractable problem from a reinforcement learning perspective. We provide a high level connection between ELBO in Bayesian Compression and the expected returns in reinforcement learning. We focus on the computing gradients of expectations to further reduce the variance of the unbiased reinforce estimator.

3.2. Enhanced Bayesian Compression via Deep Reinforcement Learning

Let us revisit the parameterized model $p(\mathcal{D}, \boldsymbol{w}) = p(\mathcal{D}|\boldsymbol{w})p(\boldsymbol{w})$ and the estimated posterior $q(w|\mathcal{D})$ from the reinforcement point of view. We assign $\boldsymbol{w}$ to the codebook value c_i the following the criterions: (1) weights are assigned to the quantized values c_k controlled by agent k with the highest probability. (2) the input and output activations are highly correlated under the distribution estimated by the ith agent. Specifically, the weights assigned to a zero can be seen as pruned in the EBC framework.

$$q(w|\mathcal{D}) \sim P(\boldsymbol{w}_l \in c_i|\mathcal{D})$$
$$\propto \begin{cases} p(\boldsymbol{w}_l|c_i)(1-\mathbb{E}_{\mathcal{D}}C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out})), & \text{if } i=0 \\ p(\boldsymbol{w}_l|c_i)\mathbb{E}_{\mathcal{D}}C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out}), & \text{otherwise,} \end{cases} \tag{4}$$

where $p(\boldsymbol{w}_l|c_i) \propto \int \frac{1}{|z_i|}\mathcal{N}(\boldsymbol{w}_l|c_i,z_i^2)dz$, l is the indexed layers, and $C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out})$ is a function measuring the correlation between the input and the output of each unit. In our experiments, we simply take $C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out}) = \boldsymbol{F}^l_{in}(\boldsymbol{F}^l_{out})^T$.

For the time step $T = 1, 2, ..., t$, we denote $\mathcal{D}_t$ and $\boldsymbol{w}_t$ as the tth batch data and the corresponding model weights in the training process, respectively. We model the update of weights $\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_t$ in a deep neural network as a Markov decision process. The parameterized model $p(\mathcal{D},\boldsymbol{w})$ and estimated posterior $q(w|\mathcal{D})$ can be decompose into a product of conditional distributions easily.

$$p(\mathcal{D},\boldsymbol{w}) = p(D)\prod_{t=2}^{T} p(\boldsymbol{w}_t|\boldsymbol{w}_{t-1},\mathcal{D}_t)p(\boldsymbol{w}_1|D) \tag{5}$$

Analogously, we factor the approximated posterior recursively as follows:

$$q_\phi(\boldsymbol{w}|\mathcal{D}) = q_\phi(\boldsymbol{w}_1|\mathcal{D})\prod_{t=2}^{T} q_\phi(\boldsymbol{w}_t|\boldsymbol{w}_{t-1},\mathcal{D}_t) \tag{6}$$

$$q_\phi(\boldsymbol{w}_t|\boldsymbol{w}_{t-1},\mathcal{D}_t) \sim P(\boldsymbol{w}_{l,t} \in c_i|\mathcal{D}_t,\boldsymbol{w}_{t-1})$$
$$\propto \begin{cases} p(\boldsymbol{w}_{l,t}|c_i)(1-\mathbb{E}_{\mathcal{D}_t}C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out})), & \text{if } i=0 \\ p(\boldsymbol{w}_{l,t}|c_i)\mathbb{E}_{\mathcal{D}_t}C(\boldsymbol{F}^l_{in},\boldsymbol{F}^l_{out}), & \text{otherwise,} \end{cases} \tag{7}$$

We formulate each codebook c_i as an agent, where c_i denotes the codebook value obtained by ith agent in this layer. We fix c_0 to zero in order to involve the pruning criterion which is discussed later. For the ith agent, we also formulate a mask function m^i to group the weights and the activation in each layer. Specifically, we set the value to 1 where the corresponding value of $P(\boldsymbol{w}_l \in c_i|\mathcal{D})$ is the maximum and we get a mask m_i of the same size with $P(\boldsymbol{w}_l \in c_i|\mathcal{D})$. In each step of RL, an agent observes the state of the environment, executes an action and receives a reward, which aims to maximize the expected sum of rewards. As a result, after EBC training, the method enforces most weights of low variance are distributed very closely around the quantization target values and can thus be replaced by the corresponding value without significant loss in accuracy.

In our Enhanced Bayesian compression framework, the policy gradient suffers from a variance increase as each layer have a flexible number of agents during the training process. We present an Actor-Critic algorithm, which is illustrated in Figure 2, to collaborate with the original network and improve the policy gradient with a critic for mitigating the high variance of the reinforcement estimator. Actor-Critic aims to improve the policy with a critic, combines the benefits of both Q-learning and Policy Gradient. Actor-Critic algorithms [32] learn the policy function π_θ (a set of action probability outputs) and the value function $V_\Phi(s)$ (evaluation of a certain state) simultaneously and interactively. For a given pair of state and action at step t sampled from $\pi_\theta(a|s)$, the algorithm fits V to the sampled reward sums. Then the evaluation is defined as follows:

$$\hat{A}^\pi = r(s_t,a_t) + \gamma\hat{V}^\pi_\Phi(s'_t) - \hat{V}^\pi_\Phi(s_t) \tag{8}$$

where γ is a discount parameter. The gradient of the objective $J(\theta)$ can be formulated as

$$\Delta_\theta J(\theta) = \sum_t \Delta \log \pi_\theta(a_t|s_t)\hat{A}^\pi(s_t,a_t) \tag{9}$$

Note that when we mention the 'network' without specific declaration, we refer to the original network to be compressed. The actor network determines the centroid and the variance of the distribution based on the weights assigned to each agent and correlation between the input and output feature maps of each layer. The actor networks collaborate to estimate the optimal quantized values of the weights. Meanwhile the low variance value is forced to make sure the network weights tightly distributed around the quantized values. As a result, after the EBC training finishes, the weights can be directly replaced by the quantized value without significant accuracy drop and then get rid of the heavily re-training steps after quantization.

We denote the actor network as π_θ, which is parameterized by θ. The state function encodes the weights of the original network $\boldsymbol{w}$, mask functions m and correlation function C as a vector of statistic with lower dimensions. It takes the weights $\boldsymbol{w}_t$ and features $\boldsymbol{F}_t$ masked by m_i at the step t as input, which is denoted as:

$$s^t = \chi(\boldsymbol{w}_t,\boldsymbol{F}_t) \tag{10}$$

In our experiments, we define the state function as the mean value and standard-deviation of $m_i * \boldsymbol{w}_t$ and $m_i * C((\boldsymbol{F}_t)_{in},(\boldsymbol{F}_t)_{out})$, as well as the average classification loss on the current mini-batch. Then the actor network of the agent v_i yields an continuous action:

$$\pi^i_\theta(s^t_i) = [c^i_t, z^i_t, lr^i_t], i = 0, 2, ..., N-1 \tag{11}$$

where c^i_t and z^i_t are the codebook quantized value and the variance. lr^i_t is a significance parameter. It is noting that we always keep c_t^0 to be zero by masking it since the weights assigned to c_t^0 are pruned. In addition to the adaptive codebook values, our EBC framework allows flexible number of codebooks by adjusting the number of agents. To achieve this goal, we define two discrete actions $\{$*delete node*,*add node*$\}$ for the agent i ($i \neq 0$) at the end of each training epoch. Using a threshold on α_l as a criterion in lth layer is equivalent to delete the agent whose ratio of assigned weights is low:

$$\frac{||m^{(i)}||^1}{n^{l-1}n^l} \leq \alpha_l \tag{12}$$

To be precise, (12) specifies the sparsity of the weights assigned to an agent. Also, for lth layer we use a threshold on β_l as a criterion to split one agent with large into two:

$$\frac{max(z^{(i)})}{\sum_i z^{(i)}} \geq \beta_l \tag{13}$$

In our experiments, α_l and β_l are set to keep the same value respectively across the layers. Then we reinitialize the codebook value c_i as $c_i \pm \frac{z_i}{\sqrt{2}}$ To be precise, (13) forces the variance of the weights assigned to an agent be constrained below a threshold. where z_i denotes the variance. In our EBC framework, the long term reward of the state-action pair is related to the accumulative decrement of negative accuracy drop ($-(acc^t - acc^{t+1}) = \Delta_{acc}$) and the KL divergency approximation. We define the immediate reward at step as:

$$r^t = \sum_i lr_i p(w_t) \log(\frac{p(\boldsymbol{w}_t|\boldsymbol{w}_{t-1}, \mathcal{D}_{t-1})}{q(\boldsymbol{w}_t|\boldsymbol{w}_{t-1}, \mathcal{D}_t)} + \Delta_{acc} \tag{14}$$

The accumulative value $R_\pi^{t'} = \sum_{t=t'}^T \gamma^{t-t'} r_t + \gamma^{T-t'} \log p(\mathcal{D}|\boldsymbol{w}_1)$. The critic network uses the function Q_Φ which is parameterized by Φ to approximate the Q value function. For each agent, the critic network only outputs one value at the final layer to evaluate the action.

Recall the third output lr_i of the actor network, this parameter is in fact a learning multiplier which denotes the significance of each layer as well as each peak. This is motivated by the fact that the impact of quantization errors on the accuracy varies across layers and peaks within each layer. our proposed EBC can be optimized for quantizing all layers of a network together for flexible optimal codebooks by exploiting the learning multiplier in (14). For deep neural networks, this is feasible since layer-by-layer quantization bit precise optimization requires exponential time complexity with respect to the number of layers. To train the Actor-Critic network, we first formulate the optimization problem with respect to the critic network Φ by minimizing the Temporal difference (TD) learning error as:

$$\min_\Phi L(\Phi) = \mathbb{E}_{s,a}(Q_\Phi(s^t, a^t) - r^t - \gamma Q_\Phi(s^{t+1}, a^{t+1})^2 \tag{15}$$

Algorithm 1 : EBC

Input: Training steps T; training set $\boldsymbol{X}$; state function χ; discount factor γ;
Output: Model weights $\boldsymbol{w}$, policy parameters θ of the actor network and the value parameters Φ of the critic network.
Initialize $\boldsymbol{w}$, θ, Φ
// update strategy for ith agent of layer l
for $t = 1$ **to** T **do**
  Sample a batch data $\boldsymbol{x}_p \in X$
  Encode the state vector: $s_i^t = \chi(\boldsymbol{w}_t, \boldsymbol{F}_t^p)$
  // actor network outputs an action
  Update the codebook value: $c_i^t = \pi_\theta(s_i^t)$
  Update the model parameters $\boldsymbol{w}$ by back-propagation.
  // update critic network
  Compute reward r^t using (14)
  Compute (15) and update Φ using (16)
  // update actor network
  Sample a batch data $\boldsymbol{x}_q \in X$ and $q \neq p$
  Encode the state vector: $s_i^{t+1} = \chi(\boldsymbol{w}_t, \boldsymbol{F}_t^q)$
  Compute $a_j^{t+1} = \pi_\theta(s_j^{t+1})$
  Update θ using (17)
end for
Delete or Add an agent using (12) and (13)

We update the parameters of the network Φ as follows:

$$\Phi = \Phi - \mu_\Phi \frac{\partial L(\Phi)}{\partial \Phi} \tag{16}$$

We update the parameters θ to output the action with the largest Q value, which is formulated as:

$$\theta = \theta - \mu_\theta \frac{\partial Q_\Phi(s^{t+1}, a^{t+1})}{\partial a} \frac{\partial \pi_\theta(s^{t+1})}{\partial \theta}|_{a=\pi_\theta(s)} \tag{17}$$

During the EBC training in each epoch, we update the codebook values and the significance parameters according to the Actor-Critic network while keeping the length of each codebook unchanged. After training of one epoch is finished, the codebook length is updated by adding or deleting the agents in each layer.

Algorithm 1 summarizes the learning procedure of our EBC.

4. Experiments

We conducted experiments on three different datasets including MNIST [36], CIFAR-10 [34] and ImageNet [12] to show the effectiveness of our method. For MNIST, we applied our EBC to LeNet [37] and compared the results obtained by our EBC with recent state-of-the-art network compression methods. For CIFAR-10, we applied our EBC to VGG-16 [52] and ResNet-18 [19] and reported the results. For ImageNet, we applied our EBC to ResNet-18 [19] and reported the results.

4.1. Implementation Details

We trained EBC in an iterative manner, where the original network and the Actor-Critic network were trained collaboratively. The Actor-Critic algorithm are operated on mini-batches, each step is a mini batch in our experiments. We define the state function χ as mean value and standard-deviation of $m_i * \boldsymbol{w}_t$ and $m_i * C((\boldsymbol{F}_t)_{in}, (\boldsymbol{F}_t)_{out})$, as well as the average classification loss on the current mini-batch, which encodes the input as a state vector with 5 elements. The thresholds α and β in (12) and (13) are set to 1e-3 and 0.3, respectively. The actor network in our experiment is a two-layer long short-term memory (LSTM) [21] network with 20 units in each layer. We specified the critic network as a simple neural network with one hidden layer and 10 hidden units. We use the Adam optimizer [30] with a learning rate of 0.001 and a discount of γ (set as 0.95) to train the Actor-Critic network. We implemented our methods in Python using Pytorch library and conducted all the experiments on GeForce GTX 1080 Ti GPU with 11GB VRAM. During training, EBC gets rid of the warm-up [54] strategy for the KL divergency term used by existing Bayesian compression methods, since the actor network output lr_t^i automatically determines the significance parameter which helps in avoiding bad local optima. At the end of the network train epochs, we obtain codebooks of different lengths for each layer via Actor-Critic network. We adopted a quantization step by assigning the weights to their closest codebook values and then remove Actor-Critic network. Having completed the training procedure of EBC, we employ the compressed network for inference directly, where the Actor-Critic network s not required.

4.2. Results on MNIST

MNIST [36] is a database of handwritten digits which is widely used to experimentally evaluate machine learning methods. We conducted the image preprocessing by subtracting the mean value and dividing by the standard-deviation over the training set. Following the same settings with [42], we demonstrate our method on two models: LeNet-300-100 [37] and LeNet-5. LeNet-300-100 is a feedforward neural network with three fully connected layers. LeNet-5 is a conventional CNN model which consists of 4 learnable layers, including 2 convolutional layers and 2 fully connected layers. For both LeNet-300-100 and LeNet-5, we train the full precision model using the standard SGD method for 20 epochs to obtain the original top-1 test error 1.6% and 0.9%.

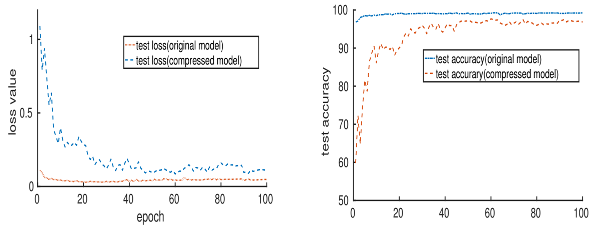
The proposed EBC method can be both applied to fine-tuning a pre-trained networks and training the networks from scratch. On MNIST, we trained both LeNet-300-100 and LeNet-5 using EBC from scratch, where all the weights are randomly initialized. The batch size is 128 and the total epoch is 200. Figure 3 shows the comparison of test loss and accuracy between the original LeNet-5 and the compressed LeNet-5 during the first 100 epochs. We denote the original model here as the model trained by our EBC without quantized to the codebooks. We find that during the first few epochs, the accuracy of compressed models drops a lot after quantized the original model. As the epochs increase, the original model converges collaborated with the Actor-Critic Network and weights of each layer are enforced to

Table 1. Results on the dataset using LeNet-300-100, showing the top-1 test error, the percentage of non-pruned weights and the bit-precision per parameter. Original is the uncompressed pre-trained model. DC corresponds to Deep Compression method [17], DNS to the method of [16], SWS to the Soft-Weight Sharing of [55], Sparse VD to the variational dropout method at [45], BC refers to BC-GHS version in Bayesian Compression in [42], BNN refers to Binarized Neural networks in [25]

Method	Test error(%)	$\frac{\|\boldsymbol{w}\neq 0\|}{\|\boldsymbol{w}\|}(\%)$	Bits
Original	1.6	100	32
DC	1.6	8.0	8-9
DNS	2.0	1.8	–
SWS	1.9	4.3	3
Sparse VD	1.8	2.2	8-14
BC	1.8	0.6	10-13
BNN	2.4	–	1
EBC	1.8	1.6	2

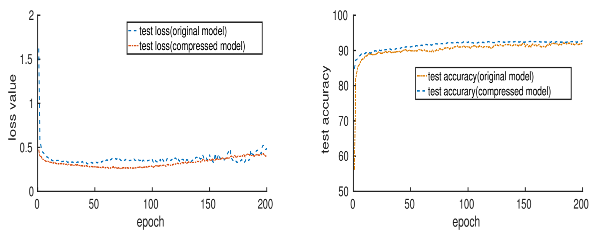
Table 2. Results on the dataset using LeNet-5, showing the top-1 test error, the percentage of non-pruned weights and the bit-precision per parameter. Original is the uncompressed pre-trained model. DC corresponds to Deep Compression method [17], DNS to the method of [16], SWS to the Soft-Weight Sharing of [55], Sparse VD to the variational dropout method at [45], BC refers to BC-GHS version in Bayesian Compression in [42], BNN refers to Binarized Neural networks in [25]

Method	Test error(%)	$\frac{\|\boldsymbol{w}\neq 0\|}{\|\boldsymbol{w}\|}(\%)$	Bits
Original	0.9	100	32
DC	0.7	8.0	10-13
DNS	0.9	0.9	–
SWS	1.0	3	3
Sparse VD	1.0	0.7	8-13
BC	1.0	0.6	10-14
BNN	1.2	–	1
EBC	1.0	0.7	2



(a) comparison of test loss (b) comparison of test accuracy

Figure 3. Comparison of test loss and accuracy between the original LeNet-5 and the compressed LeNet-5 during the first 100 epochs on MNIST dataset.



(a) comparision of test loss (b) comparision of test accuracy

Figure 4. Comparison of test loss and accuracy between the original VGG-16 and the compressed VGG-16 during the first 200 epochs on CIFAR-10 dataset.

Table 3. Results on the dataset CIFAR-10 using VGG-16, showing the top-1 test error, the percentage of non-pruned weights and the bit-precision per parameter. Original is the uncompressed pretrained model. BC refers to BC-GNJ version in Bayesian Compression in [42], BNN refers to Binarized Neural networks in [25]

Method	Test error(%)	$\frac{\lvert\boldsymbol{w}\neq0\rvert}{\lvert\boldsymbol{w}\rvert}(\%)$	Bits
Original	8.4	100	32
BC	8.6	6.7	5-11
BNN	10.2	–	1
EBC	8.8	8.0	3-4

Table 4. Results on the dataset CIFAR-10 using and ResNet-18, showing the top-1 test error, the percentage of non-pruned weights and the bit-precision per parameter. Original is the uncompressed pre-trained model. BC refers to BC-GNJ version in Bayesian Compression in [42], BNN refers to Binarized Neural networks in [25]

Method	Test error(%)	$\frac{\lvert\boldsymbol{w}\neq0\rvert}{\lvert\boldsymbol{w}\rvert}(\%)$	Bits
Original	6.8	100	32
BC	7.5	4.4	5-17
BNN	10.8	–	1
SWS	8.3	7.3	3
EBC	7.2	3.5	3-4

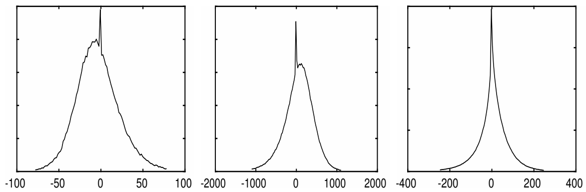
distributed tightly around the quantized values given by the actor network. Having completed the EBC training, we obtain a network which can be directly quantized (quantized to 0 means pruning) without a noticeable accuracy drop and the quantized model can be directly applied to the classification task in no need of finetuning. Table 1 and Table 2 show the results compared with the state-of-the-art compression methods. We denote the original model in the tables as the pretrained LeNet model in the table. Our method achieves a very low bit precision with a small accuracy loss (0.2% and 0.1%). The codebooks length determined by agents of each layer of both LeNet-300-100 and LeNet-5 are 3 (2bit) for all layers after convergency of the EBC. We also compared our EBC with BNN which extremely quantizes the weights to 1 bit on LeNet-300-100 and LeNet-5 trained by Theano [4]. The result shows that BNN suffers from a higher accuracy drop than ours because of a fixed quantization value.

4.3. Results on CIFAR-10

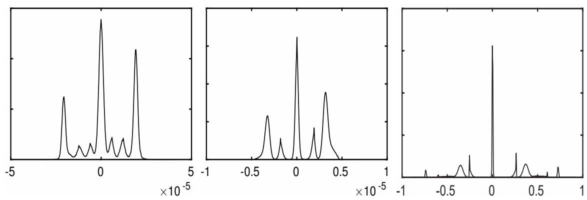
We demonstrate our method with VGG-16 [52] and ResNet-18 [19] on the CIFAR-10 dataset [34]. VGG-16 has 13 convolutional layers and more parameters and ResNet-18 is a 18 layer version of ResNet which has batch normalization layers and shortcut connections. We trained the full precision model using the standard SGD method for 200 epochs to obtain the original top-1 test error 7.1% and 6.8%. To help the EBC training converge faster, we pretrained the two models for 100 epochs using Adam and obtain top-1 test error 15.6% and 14.7% on CIFAR-10, respectively. Figure 4 shows the comparison of test loss and accuracy between the original VGG-16 and the compressed VGG-16 keep consistent even at the first few epochs because of the usage of pretrained model accelerates the convergency. Table 3 and Table 4 shows the results compared with Bayesian Compression, where the required bit-precision per layer is determined via posterior uncertainty without explicitly enforcing to learn codebooks for quantization. Our method achieves the lower bit precision than Bayesian Compression with a small accuracy loss (0.4% for VGG-16 and 1.4% for ResNet-18). The codebooks length determined by agents of each layer of VGG-16 ranges from 5 to 11 (3-4 bits) while ResNet-18 ranges from 7-13 (3-4 bit).

4.4. Results on ImageNet

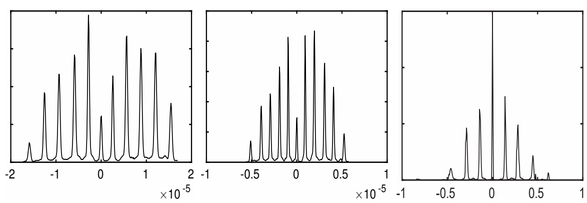
ImageNet is a large dataset covering 1,000 categories for visual recognition. It contains over 1.2M images in the training set and 50K images in the validation set. For this dataset, we report both Top-1 and Top-5 validation accuracy. On this dataset, we compare our EBC with the recent proposed low-bits methods: BWN [49], TWN [38], TTQ [60] to demonstrate the effectiveness of flexible codebooks. We cannot directly compare the related Bayesian methods since the authors do not report results on Ima-



(a) Distribution of pretrained model.



(b) Distribution of EBC trained model at epoch 100.



(c) Distribution of EBC trained model at epoch 200.

Figure 5. Visualization of the weights distribution in the conv3, conv5 and conv7 layer (from left to right) of pretrained VGG-16 on CIFAR-10 at 200th epoch (from top to bottom), EBC trained model at 100th epoch and EBC trained model at 200th epoch.

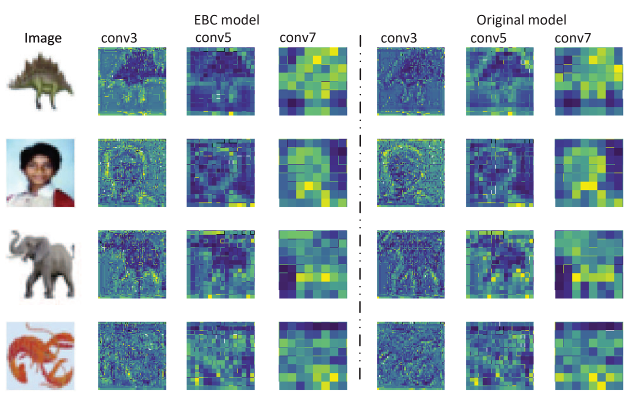


Figure 6. Visualization of the original images, the feature maps of the conv3, conv5 and conv7 layers of EBC models and original models (VGG-16), respectively. The presented feature maps are averaged over the channels.

geNet. We trained the full precision model using the standard SGD method for 100 epochs to obtain the original top-1 and top-5 validation error 31.6% and 11.3%. The results are summarized in Table 5. We see that our EBC trained model with flexible bit-precision performs better than BNN-like methods on ImageNet with memory only exceeding a little.

Table 5. Results on the dataset ImageNet using ResNet-18, showing the top-1 and top-5 validation error, the percentage of non-pruned weights and the bit-precision per parameter. Original is the uncompressed pre-trained model.

Method	Val error(Top-1/Top-5)(%)	Bits
Original	31.6/11.3	32
BWN	39.2/17.0	1
TWN	34.5/14.0	2
TTQ	34.1/13.8	2
SWS(I)	34.2/13.5	3
EBC	31.8/11.4	3-4

4.5. Visualization

Figure 5 shows the visualization of the weights distribution in the conv3 layer, conv5 layer and conv7 layer of pretrained VGG-16 at 200th epoch, EBC trained model at 100th epoch and EBC trained model at 200th epoch. We see that the weights distribution of each peak is more tight as the EBC training epoch increases.

We have also visualized the functionality of our EBC models by calculating average feature maps produced by convolution layers since the spatial feature maps of CNNs shows where the network focuses hence influence the final classification results of the given images. The results are shown in Figure 6. From the figure, we see that the feature maps of the compressed layers are very close to that of the original ones, even with a large reduction on model weights.

5. Conclusion

In this paper, we have proposed a enhanced reinforcement learning method to flexibly compress the deep network via reinforcement learning. An Actor-Critic network, which collaborates with the original network, is exploited to learn flexible codebooks in each layer for an optimal network quantization. With our EBC method, the model doesn't require re-training after the quantization. Experimental results on three datasets have been presented to demonstrate the effectiveness of our method.

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References

[1] A. Almahairi, N. Ballas, T. Cooijmans, Y. Zheng, H. Larochelle, and A. C. Courville. Dynamic capacity networks. In *ICML*, pages 2549–2558, 2016.

[2] H. B. Ammar, E. Eaton, P. Ruvolo, and M. Taylor. Online multi-task learning for policy gradient methods. In *ICML*, pages 1206–1214, 2014.

[3] A. Ashok, N. Rhinehart, F. Beainy, and K. M. Kitani. N2N learning: Network to network compression via policy gradient reinforcement learning. *ICLR*, abs/1709.06030, 2017.

[4] F. Bastien, P. Lamblin, R. Pascanu, J. Bergstra, I. Goodfellow, A. Bergeron, N. Bouchard, D. Warde-Farley, and Y. Bengio. Theano: new features and speed improvements. *arXiv preprint arXiv:1211.5590*, 2012.

[5] E. Bengio, P. Bacon, J. Pineau, and D. Precup. Conditional computation in neural networks for faster models. *CoRR*, abs/1511.06297, 2015.

[6] Y. Bengio, N. Léonard, and A. C. Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. *CoRR*, abs/1308.3432, 2013.

[7] A. Blum, N. Haghtalab, and A. D. Procaccia. Variational dropout and the local reparameterization trick. In *NIPS*, pages 2575–2583, 2015.

[8] T. Bolukbasi, J. Wang, O. Dekel, and V. Saligrama. Adaptive neural networks for fast test-time prediction. *CoRR*, abs/1702.07811, 2017.

[9] Q. Cao, L. Lin, Y. Shi, X. Liang, and G. Li. Attention-aware face hallucination via deep reinforcement learning. In *CVPR*, pages 690–698, 2017.

[10] F. Chollet. Xception: Deep learning with depthwise separable convolutions. In *CVPR*, pages 1800–1807, 2017.

[11] M. Courbariaux, Y. Bengio, and J. David. Binaryconnect: Training deep neural networks with binary weights during propagations. In *NIPS*, pages 3123–3131, 2015.

[12] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and F. Li. Imagenet: A large-scale hierarchical image database. In *CVPR*, pages 248–255, 2009.

[13] Y. Gong, L. Liu, M. Yang, and L. D. Bourdev. Compressing deep convolutional networks using vector quantization. *CoRR*, abs/1412.6115, 2014.

[14] A. Graves and N. Jaitly. Towards end-to-end speech recognition with recurrent neural networks. In *ICML*, pages 1764–1772, 2014.

[15] S. Gu, T. Lillicrap, I. Sutskever, and S. Levine. Continuous deep q-learning with model-based acceleration. In *ICML*, pages 2829–2838, 2016.

[16] Y. Guo, A. Yao, and Y. Chen. Dynamic network surgery for efficient dnns. In *NIPS*, pages 1379–1387, 2016.

[17] S. Han, H. Mao, and W. J. Dally. Deep compression: Compressing deep neural network with pruning, trained quantization and huffman coding. *CoRR*, abs/1510.00149, 2015.

[18] S. Han, J. Pool, J. Tran, and W. J. Dally. Learning both weights and connections for efficient neural networks. *CoRR*, abs/1506.02626, 2015.

[19] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *CVPR*, pages 770–778, 2016.

[20] Y. He, J. Lin, Z. Liu, H. Wang, L. Li, and S. Han. AMC: automl for model compression and acceleration on mobile devices. In *ECCV*, pages 815–832, 2018.

[21] S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[22] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *CoRR*, abs/1704.04861, 2017.

[23] G. Huang, S. Liu, L. van der Maaten, and K. Q. Weinberger. Condensenet: An efficient densenet using learned group convolutions. *CoRR*, abs/1711.09224, 2017.

[24] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger. Densely connected convolutional networks. In *CVPR*, pages 2261–2269, 2017.

[25] I. Hubara, M. Courbariaux, D. Soudry, R. El-Yaniv, and Y. Bengio. Binarized neural networks. In *NIPS*, pages 4107–4115, 2016.

[26] I. Hubara, M. Courbariaux, D. Soudry, R. El-Yaniv, and Y. Bengio. Quantized neural networks: Training neural networks with low precision weights and activations. *CoRR*, abs/1609.07061, 2016.

[27] F. N. Iandola, M. W. Moskewicz, K. Ashraf, S. Han, W. J. Dally, and K. Keutzer. Squeezenet: Alexnet-level accuracy with 50x fewer parameters and $<$1mb model size. *CoRR*, abs/1602.07360, 2016.

[28] B. Jacob, S. Kligys, B. Chen, M. Zhu, M. Tang, A. G. Howard, H. Adam, and D. Kalenichenko. Quantization and training of neural networks for efficient integer-arithmetic-only inference. *CoRR*, abs/1712.05877, 2017.

[29] F. Juefei-Xu, V. N. Boddeti, and M. Savvides. Local binary convolutional neural networks. In *CVPR*, pages 4284–4293, 2017.

[30] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014.

[31] D. P. Kingma and M. Welling. Auto-encoding variational bayes. *CoRR*, abs/1312.6114, 2013.

[32] V. R. Konda and J. N. Tsitsiklis. Actor-critic algorithms. In *NIPS*, pages 1008–1014, 1999.

[33] X. Kong, B. Xin, Y. Wang, and G. Hua. Collaborative deep reinforcement learning for joint object search. In *CVPR*, 2017.

[34] A. Krizhevsky and G. Hinton. Learning multiple layers of features from tiny images. 2009.

[35] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, pages 1097–1105, 2012.

[36] Y. LeCun. The mnist database of handwritten digits. *http://yann. lecun. com/exdb/mnist/*, 1998.

[37] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[38] F. Li and B. Liu. Ternary weight networks. *CoRR*, abs/1605.04711, 2016.

[39] H. Li, Z. Lin, X. Shen, J. Brandt, and G. Hua. A convolutional neural network cascade for face detection. In *CVPR*, pages 5325–5334, 2015.

[40] X. Liang, L. Lee, and E. P. Xing. Deep variation-structured reinforcement learning for visual relationship and attribute detection. In *CVPR*, pages 848–857, 2017.

[41] L. Liu and J. Deng. Dynamic deep neural networks: Optimizing accuracy-efficiency trade-offs by selective execution. *CoRR*, abs/1701.00299, 2017.

[42] C. Louizos, K. Ullrich, and M. Welling. Bayesian compression for deep learning. In *NIPS*, pages 3290–3300, 2017.

[43] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

[44] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533, 2015.

[45] D. Molchanov, A. Ashukha, and D. P. Vetrov. Variational dropout sparsifies deep neural networks. In *ICML*, pages 2498–2507, 2017.

[46] K. Neklyudov, D. Molchanov, A. Ashukha, and D. P. Vetrov. Structured bayesian pruning via log-normal multiplicative noise. In *NIPS*, pages 6778–6787, 2017.

[47] A. Odena, D. Lawson, and C. Olah. Changing model behavior at test-time using reinforcement learning. *CoRR*, abs/1702.07780, 2017.

[48] Y. Rao, J. Lu, and J. Zhou. Attention-aware deep reinforcement learning for video face recognition. In *ICCV*, pages 3931–3940, 2017.

[49] M. Rastegari, V. Ordonez, J. Redmon, and A. Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks. In *ECCV*, pages 525–542, 2016.

[50] L. Sifre and P. Mallat. *Rigid-motion scattering for image classification*. PhD thesis, Citeseer, 2014.

[51] D. Silver, G. Lever, N. Heess, T. Degris, D. Wierstra, and M. Riedmiller. Deterministic policy gradient algorithms. In *ICML*, pages 387–395, 2014.

[52] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[53] R. Socher, C. C. Lin, A. Y. Ng, and C. D. Manning. Parsing natural scenes and natural language with recursive neural networks. In *ICML*, pages 129–136, 2011.

[54] C. K. Sønderby, T. Raiko, L. Maaløe, S. K. Sønderby, and O. Winther. Ladder variational autoencoders. In *NIPS*, pages 3738–3746, 2016.

[55] K. Ullrich, E. Meeds, and M. Welling. Soft weight-sharing for neural network compression. *ICLR*, 2017.

[56] H. Van Hasselt, A. Guez, and D. Silver. Deep reinforcement learning with double q-learning. In *AAAI*, pages 2094–2100, 2016.

[57] L. Yu, W. Zhang, J. Wang, and Y. Yu. Seqgan: Sequence generative adversarial nets with policy gradient. In *AAAI*, pages 2852–2858, 2017.

[58] X. Zhang, X. Zhou, M. Lin, and J. Sun. Shufflenet: An extremely efficient convolutional neural network for mobile devices. *CoRR*, abs/1707.01083, 2017.

[59] A. Zhou, A. Yao, Y. Guo, L. Xu, and Y. Chen. Incremental network quantization: Towards lossless cnns with low-precision weights. *CoRR*, abs/1702.03044, 2017.

[60] C. Zhu, S. Han, H. Mao, and W. J. Dally. Trained ternary quantization. *CoRR*, abs/1612.01064, 2016.

[61] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le. Learning transferable architectures for scalable image recognition. *CoRR*, abs/1707.07012, 2017.