Automated Model Compression by Jointly Applied Pruning and Quantization

Wenting Tang,1 Xingxing Wei,1 Bo Li1
1 Beijing Key Laboratory of Digital Media, School of Computer Science and Engineering, Beihang University Beijing, China
wtang13@buaa.edu.cn, xxwei@buaa.edu.cn, boli@buaa.edu.cn

Abstract

Although deep neural networks (DNNs) achieve excellent performance in real-world computer vision tasks, network compression may be necessary to adapt DNNs into edge devices such as mobile phones. In the traditional deep compression framework, iteratively performing network pruning and quantization can reduce the model size and computation cost to meet the deployment requirements. However, such a step-wise application of pruning and quantization may lead to suboptimal solutions and unnecessary time consumption. In this paper, we tackle this issue by integrating network pruning and quantization as a unified joint compression problem, and then use AutoML to automatically solve it. We find the pruning process can be regarded as the channel-wise quantization with 0 bit. Thus, the separate two-step pruning and quantization can be simplified as the one-step quantization with mixed precision. This unification not only simplifies the compression pipeline but also avoids the compression divergence. To implement this idea, we propose the Automated model compression by Jointly applied Pruning and Quantization (AJPQ). AJPQ is designed with a hierarchical architecture: the layer controller controls the layer sparsity and the channel controller decides the bitwidth for each kernel. Following the same importance criterion, the layer controller and the channel controller collaboratively decide the compression strategy. With the help of reinforcement learning, our one-step compression is automatically achieved. Compared with the state-of-the-art automated compression methods, our method obtains a better accuracy while reducing the storage considerably. For fixed precision quantization, AJPQ can reduce more than 5× model size and 2× computation with a slight performance increase for Skynet in the remote sensing object detection. When mixed precision is allowed, AJPQ can reduce 5× model size with only 1.06% top-5 accuracy decline for MobileNet in the classification task.

Introduction

Although deep neural networks (DNNs) achieve excellent performance in real-world computer vision tasks, network compression may be necessary to adapt DNNs into edge devices such as mobile phones and surveillance camera (Zou et al. 2019). To obtain a balance between the model’s performance and reduction, different approaches of model compression are proposed such as knowledge distillation, network pruning and binary convolutional network (Hinton, Vinyals, and Dean 2015; Han et al. 2015; Rastegari et al. 2016), etc.

Either network pruning or network quantization can achieve model compression by reducing the size or bitwidth of weights. However, those compression techniques sometimes can be heavy-duty of human work requiring a tedious parameter adjusting process. Although some criterions (Li et al. 2017; Han et al. 2015) can help to identify redundant connections during pruning, it may involve manual work to decide proper layer sparsity. Likewise, when mixed precision (Elthakeb et al. 2018) is introduced to fully leverage advantages of the cutting-edge hardware, the appropriate combination of each layer’s or kernel’s bitwidth needs to be manually explored. To address this issue, the AutoML technique is introduced to perform automated compression (He et al. 2018; Manessi et al. 2018; Wang et al. 2019; Gao et al. 2019). In these methods, the deep compression framework proposed by Han, Mao, and Dally (2016) contains a three stage pipeline: pruning, quantization and Huffman coding to reduce the storage step by step. To further improve the performance for each step, they utilize the AutoML(Automated Machine Learning) to perform automated pruning (He et al. 2018) and automated quantization (Wang et al. 2019), respectively.

Figure 1 illustrates the framework of the deep compression. In the pruning phase, deep compression takes the original network as input, and then removes the unnecessary connections, outputting a pruned model. In the quantization phase, deep compression takes the pruned network as input, and then produces a nearly lossless compressed model represented by the integer weights. In each phase, the optimal compression can be achieved because the AutoML technique can search the most available compression strategy according to hardware constraint. However, in the view of the whole compression, this simple combination of pruning and quantization is suboptimal. The pruning and quantization should interact with each other to achieve the global optimal balance between the performance holding and computation reduction, rather than their own optimum. What’s more, because two optimization problems need solving, this step-wise design is time consuming.

To tackle this issue, we incorporate the pruning and quan-
Deep Compression Framework

Joint Compression Framework

Figure 1: The deep compression (Han, Mao, and Dally 2016) and our joint compression. The deep compression framework applies network pruning and quantization step by step, which means network quantization only starts when pruning finish. Based on compression requirements, our joint compression framework can spontaneously switch among different compression techniques for different layers.

Joint Compression Framework

One-step: channel-wise quantization

Figure 2: Overview of the Automated Model Compression by Jointly applied Pruning and Quantization (AJPQ) engine. For specific compression requirements and a model, AJPQ searches the quantization plan layer by layer. At each layer, the layer controller decides the layer sparsity, and then the kernel controller determines the bit-width for preserved channels. After searching the quantization plan for specific episodes, AJPQ outputs a compressed model by the quantization plan with the highest reward.

Discussion and Conclusion

In summary, our contributions can be concluded in the three aspects:

1) A joint compression framework is proposed to accelerate the searching for a globally optimal compression strategy while retaining the performance of the compressed model.

2) We propose a new viewpoint that pruning process can be regarded as the channel-wise quantization with 0 bit, and furthermore, gives a hierarchical architecture to efficiently and automatically solve the channel-wise quantization with mixed precision.

3) We evaluate AJPQ approach with the state-of-the-art automated compression tools AMC (He et al. 2018) and HAQ (Wang et al. 2019) on MobileNet (Howard et al. 2017) and Skynet. A better performance with less time consumption is achieved. What’s more, AJPQ can reduce more than 5× model size and 2× computation while achieving the performance with 4.5% improvement for Skynet in the remote sensing object detection.

The following sections are organized as follows: previous work in network compression is summarized in Related Work, detailed design of AJPQ is presented in Methodology, effectiveness of AJPQ for the classification and detection is presented in Experimental Results, conclusion and further improvement is in Conclusion.
Related Work

As network pruning can be defined as a channel selection problem followed by a specific criterion, extensive works focus on evaluating the redundancy or importance of channels. For example, the weight values of connections are initially used to evaluate the importance of connections in a trained model (Li et al. 2017), Han et al. 2015, He et al. 2019, Zhuang et al. 2018, Ye et al. 2018). In contrast to directly utilizing trained weights, He et al. (2019) represent the common information by geometric median among filters as an attempt to overcome the “small norm deviation” and “large minimum norm” problems brought by the norm-based criterion (Li et al. 2017). Anwar, Hwang, and Sung (2017) identify the trivial and redundant connection by a genetic algorithm to adapt to the different pruning particle. Although these criteria are efficient in computation and application, defining preserve ratio or sparsity for each layer is manual work.

To get rid of the tedious process of parameter adjustment, (Zhuang et al. 2018, Ye et al. 2018, Liu et al. 2019, Luo, Wu, and Lin 2017, Zhu and Gupta 2018, Gao et al. 2019) train a pruned network from the scratch. For example, (Zhuang et al. 2018) augment the meaning of channel importance with the discriminative power. Ye et al. (2018) form the channel selection as an optimization problem and solve it by ISTA (Iterative Shrinkage-Thresholding Algorithm) in batch normalization applied DNNs. Inspired by NAS (Zoph and Le 2017), (Liu et al. 2019) keeps the model with the best performance from a set of random generated pruned models.

As the pruning process can be defined as a Markov decision process (Bertsekas 1995), techniques in AutoML (Automated Machine Learning) domain are applied to efficiently search the compression plan in a layer-by-layer manner (Elthakeb et al. 2018, He et al. 2018, Wang et al. 2019, Ashok et al. 2018). To support deep quantization which allows mixed precision in network representation, HAQ and ReLeQ (Wang et al. 2019, Elthakeb et al. 2018) are proposed while ReLeQ (Elthakeb et al. 2018) requires a fine-tuning stage beside the reinforcement learning searching loop. Those reinforcement learning approaches enable more controls during pruning or quantization related schedule process.

After deep compression framework (Han, Mao, and Dally 2016), plenty of works are inspired (Manessi et al. 2018, He et al. 2018, Chen, Emer, and Sze 2017, Wen et al. 2016, Zhu and Gupta 2018). For example, (Manessi et al. 2018, He et al. 2018) and (Zhu and Gupta 2018) aim to automatically prune connections. While Manessi et al. (2018) improve the threshold-based channel selection in (Han, Mao, and Dally 2016), (Zhu and Gupta 2018) and (He et al. 2018) schedule preserve ratio for each layer by a sparsity function and RL agent respectively. To achieve a considerable reduction in convolutional layers of the pruning process in deep compression, (Wen et al. 2016) proposes to learn the structured sparsity. Utilizing the deep compression framework, (Chen, Emer, and Sze 2017) deploys an energy-efficient model for real-world application.

There are also explorations to achieve one-step compression without following the deep compression framework such as NAS (Neural architecture search) (Zoph and Le 2017) and binary convolutional network (Rastegari et al. 2016). Considering the high computations resource requirements, NAS may not be an economical solution for general usage. The binary convolutional network may be the answer, but it cannot replace all existing useful DNNs so far.

Overall, AJPQ automatically achieves the pruning and quantization in the one-step compression, which is different from the above works.

![Figure 3: Roles for layer and channel controller in our method. Guided by the same importance criterion at each layer, the agent generates a quantization plan to deliver positive reward with respect to the performance and compression. The quantization plan is generated by the layer controller and the channel controller together: the layer controller decides channels with zero bit-width; the controller decides non-zero bit-width for the preserved channels.](image)

Methodology

Following the joint compression framework, the AJPQ is proposed for searching the quantization plan. The layer-wise searching for a proper quantization plan can be formulated as a dynamic programming problem. Considering a DNN model with \( n \) quantizable layers and the channel number for each layer is represented by \( I_l, \) \( l = 1, \ldots, n \), thus \( I = \{I_1, \ldots, I_n\}, \) our goal is to balance the performance and storage by assigning each channel with the proper bitwidth. Let us denote that \( s_l \) is an environment state, \( P^l \) is a channel-wise quantization plan, \( r_l \) is the reward of the generated channel-wise quantization plan. We assume that \( r_0, r_1, \ldots, r_{n-1} \) are independent. Thus, the quantization state changes as follows:

\[
s_{l+1} = f(s_l, P^l, r_l)
\]  

(1)

For the \( l \)-th layer, the problem space is \((\text{bit}_{\max} + 1)^l\) with allowed the bitwidth in \([0, \text{bit}_{\max}]\), where the \( \text{bit}_{\max} \) is the maximal allowed bitwidth and is set as 8 in default. Because \((\text{bit}_{\max} + 1)^l\) is very large, the amount of the possible permutations of \( P^l \) is massive. The previous work has shown
that eliminating the redundant channels in a trained model is nearly lossless (He et al. 2019), thus, removing the trivial channels will make the problem space shrink. A widely used metric to measure the channel’s redundancy is the importance score \( \{\text{imp}_{l} \}_{l = 1, ..., I} \), which is computed by the \( L_1 \)-norm of the corresponding kernel values in the \( l \)-th layer (Li et al. 2017). For the preserved channels, we narrow the searching space by the assumption that the more important a channel is, the longer bitwidth it should hold. Therefore, by using the identical importance score \( \text{imp}_{l} \), the minimal bitwidth \( \text{minbit}_{l} \) is computed for the \( c \)-th preserved channel. \( \text{minbit}_{l} \) is used as the lower bound in the searching, and the upper bound is \( \text{bit}_{max} \). So the problem space is shrunk to \( \prod_{c=1}^{C} (\text{bit}_{max} - \text{minbit}_{c}) \), where \( c_{nz} \) is the number of nonzero bitwidth channels. With the approaching goal and a narrowed searching space, the non-zero mixed bitwidths \( B = \{b_{1}, ..., b_{cnz}\} \) for the preserved channels should be solved by a greedy algorithm without dramatic performance decline. In this way, this dynamic programming problem is efficiently optimized.

Specifically, the layer controller in our method identifies the redundancy, and predicts the layer sparsity by DDPG (Silver et al. 2014). The channel controller performs channel selection and decides the different bitwidths for the nontrivial channels by a greedy algorithm.

Layer Controller

Reinforcement learning is deployed for identifying layer sparsity \( a_{l} \), which means the ratio between the number of nonzero bit channels and the total amount of original channels. As we define that \( a_{l} \in (0, 1] \), the DDPG algorithm is used to solve the continuous action space of \( a_{l} \).

**State Space:** The state space \( \mathcal{M} = \{s_{l}|l = 1, ..., n\} \) is a finite set consisting of all quantizable layers for the model to be compressed. The state \( s_{l} \) is characterized by the following features:

\[
(idx, t, c_{o}, c_{i}, w, h, stride, k, \text{reducedFLOPs}, \text{restFLOPs}, \text{reducedSize}, \text{restSize}, a_{l-1})
\]  

(2)

where for a quantizable layer, \( idx \) is the index, \( t \) is the type of layer (fully connected layer or convolutional layer), \( c_{o} \) is the number of output channels and \( c_{i} \) is the number of input channels. \( w, h \) are width and height for each input feature map. \( stride, k \) are the value of the stride and kernel size which will be 0 and 1 for fully connected layer, respectively. \( \text{reducedFLOPs} \) and \( \text{restFLOPs} \) are the numbers of the reduced and the rest FLOPs for the current quantization plan; \( \text{reducedSize} \) and \( \text{restSize} \) are the amounts of the reduced and the rest storage for the current quantization plan. The state is normalized at each update because it is friendly for actor and critic network (Ashok et al. 2018). As agent explores in a layer-by-layer manner, such features are required to seek a proper quantization plan.

**Reward:** The reward is used to evaluate the captured trade-off by comparing the performance and the model size between the compressed model \( N' \) and the original model \( N \). For \( N \) on classification task, the top-5 accuracy is \( N_{\text{acc}} \); for \( N \) on detection task, the average precision(AP) with IoU(intersection over union)=0.3 is \( N'_{\text{AP}} \). \( N_{\text{size}} \) is the original model size. Our goal is compressing model \( N \) within the \( s \times N_{\text{size}} \), where \( s \) is decided by the hardware constraints and \( s \in (0, 1] \). The reward \( r \) is derived by:

\[
r = \begin{cases} 
-10.0, & N'_{\text{size}} > s \times N_{\text{size}} \\
0.1 \times (N'_{\text{AA}} - N_{\text{AA}}), & N'_{\text{size}} \leq s \times N_{\text{size}} \\
N'_{\text{AP}} - N_{\text{AP}}, & N'_{\text{size}} \leq s \times N_{\text{size}}
\end{cases}
\]  

(3)

**Algorithm 1 Produce quantization plan for the whole network**

**Input:** \( N, N_{\text{size}}, n, T, N'_{\text{size}}, \) each layer’s size \( S, \) total searching episodes \( e, \) required model compression ratio \( sc, \) upper bound of the bitwidth \( \text{bit}_{max} \):

1: Initialize \( s_{0} \) represented by Equation (2) and the current searching episodes \( e_{\text{cur}} = 0 \)
2: while \( e_{\text{cur}} < e \) do
3: \( l = 0, P = \{\text{bit}_{max}\} \)
4: Initialize the critic network \( \mu, \) the actor network \( \theta, \) exploration noise \( \sigma = 0.9, \) each quantizable layer size \( S = \{S_{l}|l = 1, ..., n\} \) by original model \( N \)
5: while \( l < n \) do
6: \( a_{l} = T(N(\mu(s_{l}|\theta_{l}^{e})), \sigma^{2}, 0, 1)) \)
7: Compute the number of nonzero bit channels \( c_{nz} = \min\{1, \max(1, \lceil |I_{l}| \times a_{l}\rceil)\} \)
8: Compute \( \text{imp}_{l} = \sum_{j=1}^{s_{l}} |F_{ij}| \) by the value of the according filters \( F_{ij} \)
9: Sort \( \text{imp}_{l} \) in the descending order
10: Compute index of the preserved channels \( I_{nz} = \text{top}_{c_{nz}} \{\text{imp}_{l}, i = 1, ..., n\} \)
11: For \( i \not\in I_{nz}, P_{l} = 0, \text{minbit}_{l} = 0 \)
12: For \( i \in I_{nz}, \) \( P_{l} = \text{bit}_{max}, \text{minbit}_{l} = \text{bit}_{max} \times\)
13: Update \( S, N_{\text{size}} \) by quantization plan \( P_{l} \)
14: if \( l == n - 1 \) then
15: while \( N'_{\text{size}} > sc \times N_{\text{size}} \) do
16: \( l' = \max_{i \in 1, ..., n} (S_{l}) \)
17: \( c' = \min (\text{imp}_{l'}) \)
18: \( \text{if} P_{l'} > \text{minbit}_{l'}, \text{then} \)
19: \( P_{l'} = P_{l'} - 1 \)
20: end if
21: Update \( S', N_{\text{size}} \) by quantization plan \( P_{l} \)
22: end while
23: end if
24: Update reward \( r_{l} \) by Equation (3) and \( S_{l} \)
25: \( l = l + 1 \)
26: end while
27: Update layer controller with \( a_{l}, s_{l} \) by DDPG (Silver et al. 2014)
28: \( e_{\text{cur}} = e_{\text{cur}} + 1 \)
29: end while
channel controller is responsible for deciding the permutation of the bit-widths for the preserved channels. As shown in Algorithm 1, the number of preserved channels $c_{nz}$ is identified by layer sparsity $a_l$ at $l$-th layer. Then based on $c_{nz}$ and channels' importance $imp$, index of preserved channels $I_{nz}$ is identified. For greedy searching a quantization plan, the lower bound is represented by the minimal bit-width $minbit$, and the upper bound is the maximal allowed bitwidth $bit_{max}$. When the compressed model size is larger than the size constraint, the channel controller first selects a layer and then declines the bit-width from the trivial channels. The channel controller is also compatible with the layer-wise quantization and the fixed precision quantization. Either the layer-wise quantization or the fixed precision is a special case of the channel-wise quantization. What’s more, two layer selection rules are implemented in the AJPQ. The "large layer first" rule selects the layer with the largest layer size from all quantizable layers, the “deep layer first rule” adjusts the quantization plan from the deepest quantizable layer.

Joint Decision
As stated before, each layer’s quantization plan is a joint decision made by the layer controller and the channel controller. A hierarchical structure is designed to fulfill this target as shown in Figure 3. An identical importance criterion guides the process of eliminating the redundancy and preserving channels. After the layer controller deciding a layer sparsity, the channel controller acts as a regulator: retaining the preserved channels with a high bit-width when the layer sparsity is too high to maintain the performance and reducing some preserved channels’ bitwidth when the layer sparsity is too low to perform necessary compression. In this way, the elements associated with the trimmed channels’ are set to 0 bit, while the other elements are retained in the proper bit-width. Our method is concluded in Algorithm 1.

Experimental Results

Table 1: The accuracy, compressed ratio, and FLOPs ratio achieved by AMC (He et al. 2018), HAQ (Wang et al. 2019), and our method on MobileNet.

| Methods               | Accuracy (top-1) | Accuracy (top-5) | Compressed ratio (bit) | FLOPs ratio | Searching episodes |
|-----------------------|------------------|------------------|------------------------|-------------|--------------------|
| AMC+Fixed             | 66.214(5.426)    | 85.330(4.14)     | 0.2484                 | 0.8005      | 500                |
| AJPQ (Fixed)          | 67.020(4.62)     | 87.110(2.36)     | 0.214                  | 0.817       | 500                |
| AMC+HAQ (layer-wise) | 66.690(4.95)     | 85.2(4.27)       | 0.207                  | 0.8005      | 900                |
| AJPQ (layer-wise)     | 66.280(5.36)     | 87.00(2.47)      | 0.195                  | 0.808       | 500                |
| AJPQ (channel-wise)   | 69.480(2.16)     | 88.41(1.06)      | 0.189                  | 0.922       | 100                |

Table 1: The accuracy, compressed ratio, and FLOPs ratio achieved by AMC (He et al. 2018), HAQ (Wang et al. 2019), and our method on MobileNet.

Baselines

Here, different pruning and quantization methods are deployed into the deep compression framework to form the baselines in our experiments.

AMC+Fixed: The AMC (He et al. 2018) is used as the pruning component in the deep compression framework. Fixed precision is achieved by the k-means (Macqueen 1967). The bit-width of the compressed model is 8.

AMC+HAQ: To support the quantization with mixed precision, the HAQ (Wang et al. 2019) is used as the quantization component in the deep compression framework. The HAQ can perform the mixed precision across different layers, and will automatically find the available bit-width for each layer. In this way, AMC+HAQ accomplish the quantization with mixed precision.
Table 2: The accuracy, compressed ratio, and FLOPs ratio achieved by AMC (He et al. 2018), HAQ (Wang et al. 2019), and our method on SkyNet.

| Methods            | AP     | Compressed ratio (bit) | FLOPs ratio | Searching episodes |
|--------------------|--------|------------------------|-------------|--------------------|
| AMC+Fixed          | 0.682(↓ 0.021) | 0.242                 | 0.959       | 150                |
| AJPQ (Fixed)       | 0.703(↑0.001)  | 0.197                 | 0.744       | 150                |
| AMC+HAQ (layer-wise) | 0.728(↑0.025) | 0.195                 | 0.959       | 450                |
| AJPQ (layer-wise)  | 0.731(↑0.028) | 0.188                 | 0.931       | 150                |
| AJPQ (channel-wise)| 0.747(↑0.045) | 0.197                 | 1.000       | 300                |

Results and Analysis

Channel-wise Deep Quantization: As shown in Table 1, AJPQ (channel-wise) achieves the highest size reduction 0.189 and the best model performance (88.41% versus the top-5 accuracy) among all the methods with only 100 searching episodes. The slight decline in performance demonstrates that the importance criterion can guide channel-wise quantization to attain a proper trade-off among different compression techniques. After thorough exploration, the AJPQ achieves a noticeable detection performance increase by 0.045 only with quantization in Table 2. To maintain performance, the AJPQ wisely chooses the compression technique rather than simply combining the pruning and quantization.

Fixed precision: As illustrated in Table 1, AJPQ (Fixed) retains a 1.67% higher top-5 accuracy with a nearly 0.03 larger size reduction than the AMC+Fixed approach. Under the same time consumption, the AJPQ (Fixed) captures a better trade-off than the AMC+Fixed approach. This result illustrates that the deep compression framework may be trapped into sub-optimal results by making compression decisions with local knowledge. In Table 2, AMC+Fixed also achieves little size reduction on the model required a short decision trajectory. The incompleteness of the state setting for the AMC may explain the performance decline and the similar value of the compression ratio of AMC+Fixed. Because the AMC using FLOPs (floating-point operations per second) reduction as an approximation of size reduction, it cannot perform control of compression as precise as the AJPQ and end in local optimal strategy. Meanwhile, the AJPQ achieves 0.744 FLOPs reduction with 0.001 performance increase on SkyNet.

Layer-wise Deep Quantization: As demonstrated in Table 1, our AJPQ (layer-wise) achieves a 1.8% higher top-5 accuracy with a 0.012 larger size reduction than the AMC+HAQ. Taking advantage of the one-step compression, AJPQ saves nearly half of the time consumption caused by the serial compression process shown in Figure 1. For SkyNet, although the HAQ achieves performance increase by the necessary exploration for 300 searching episodes, the best result of AMC+HAQ is not the optimal compression strategy. Based on global decisions, the AJPQ reduces more storage and computation than AMC+HAQ with 0.188 compressed ratio and 0.931 FLOPs ratio. In AJPQ, we implement different layer selection rules to adjust the quantization plan: the "large layer first" in ours and the "deep layer first" rule in the HAQ. With a 0.09 higher top-1 accuracy and a 0.004 larger size reduction, our layer selection rule is more efficient than the HAQ’s as shown in Table 3.

Quantization Plan Changes During Searching

As demonstrated in Table 3, AJPQ performs to some specific compression requirements, we set the compression ratio to 0.2, and performance decline should less or equal with 0 for the classification task and detection task. As shown in Figure 4, a few layers perform quantization at the beginning. To meet the compression requirement, AJPQ tends to decrease bit-width to store weights for each layer. The best quantization plan performs more quantization in the last two layers than the other layers before. Because the fully connected (FC) layers in MobileNet contains more parameters than convolution layers. As shown in Figure 5, AJPQ tends to preserve channels rather than simply pruning. Compression is less performed on the last few layers than the former layers during the searching. Because SkyNet uses the final convolution layer as the detector, the last few layers may be responsible for delivering the extracted features.

Effectiveness evaluation of reward functions: The reward function is defined as reward = acc(N') × 0.01 in AMC and reward = (acc(N') − acc(N)) × 0.1 in HAQ,
| Methods                                | Accuracy (top-1) | Accuracy (top-5) | Compressed FLOP ratio (bit) | Searching episodes |
|----------------------------------------|------------------|------------------|----------------------------|--------------------|
| AJPQ (Deep layer first)                | 66.190           | 87.00            | 0.199                      | 500                |
| AJPQ (Large layer first)               | **66.280**       | 87.00            | **0.195**                  | **500**            |

Table 3: Performance achieved by AJPQ under different layer selection strategies.

where $\text{acc}(N)$ is the performance of the original model and $\text{acc}(N')$ is the performance of the compressed model. The performance of those reward functions is shown in Figure 6. During the search, the AMC’s rewards are hovering below the target reward. Meanwhile, the HAQ’s rewards endure great fluctuation during the first 100 episodes. The AMC reward function gives all compression plans positive feedbacks without any discrimination. Thus, it can not efficiently explore. Meanwhile, HAQ’s reward function can distinguish the strategies that can maintain performance. However, the exploration noise of the reinforcement learning agent is not the answer to the occurrences of the vibration. The small multiplier in the HAQ’s reward function may weaken the punishment effect of negative reward. Our reward function can filter the unqualified searching strategies. As shown in Figure 7, the quantization plans violating the size reduction requirement are punished with a negative reward. Thus, the further explorations can focus on retaining performance.

**Conclusion**

In this paper, we proposed AJPQ (Automated Model Compression by Jointly Applied Pruning and Quantization), which proved that collaborating quantization and pruning could obtain a better trade-off between the performance holding and computation reduction. After providing a new viewpoint of pruning and quantization, we proposed a hierarchical manner to perform the quantization with mixed precision. A variety of experiments demonstrated the effectiveness of the proposed joint compression. In the future, the improvement in compression plan scheduling may be achieved by hierarchical reinforcement learning (Hyun Jung, Won Kim, and Kim 2019).
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