GNN-RL Compression: Topology-Aware Network Pruning using Multi-stage Graph Embedding and Reinforcement Learning

Sixing Yu 1  Arya Mazaheri 2  Ali Jannesari 1

Abstract
Model compression is an essential technique for deploying deep neural networks (DNNs) on power and memory-constrained resources. However, existing model-compression methods often rely on human expertise and focus on parameters’ local importance, ignoring the rich topology information within DNNs. In this paper, we propose a novel multi-stage graph embedding technique based on graph neural networks (GNNs) to identify the DNNs’ topology and use reinforcement learning (RL) to find a suitable compression policy. We performed resource-constrained (i.e., FLOPs) channel pruning and compared our approach with state-of-the-art compression methods using over-parameterized DNNs (e.g., ResNet and VGG-16) and mobile-friendly DNNs (e.g., MobileNet and ShuffleNet). We evaluated our method on various models from typical to mobile-friendly networks, such as ResNet family, VGG-16, MobileNet-v1/v2, and ShuffleNet. The results demonstrate that our method can prune dense networks (e.g., VGG-16) by up to 80% of their original FLOPs. More importantly, our method outperformed state-of-the-art methods and achieved a higher accuracy by up to 1.84% for ShuffleNet-v1. Furthermore, following our approach, the pruned VGG-16 achieved a noticeable $1.38 \times$ speed up and 141 MB GPU memory reduction.

1. Introduction
The demand for deploying DNN models on edge devices (e.g., mobile phones, robots, and self-driving cars) are expanding rapidly. However, the increasing memory and computing power requirements of DNNs make their deployment on edge devices a grand challenge. Thus, various custom-made DNN models have been introduced by experts to accommodate a DNN model with reasonably high accuracy on mobile devices (Howard et al., 2019; Tan & Le, 2019; Zhang et al., 2018b; Ma et al., 2018; Mehta et al., 2020; Huang et al., 2018). In addition to mobile-friendly deep networks, model optimization methods such as network pruning (Han et al., 2016; He et al., 2018), factorization (Sainath et al., 2013), knowledge distillation (Hinton et al., 2015), and parameter quantization (Han et al., 2016) help to shrink the DNN model size down to the target hardware capabilities. Among such methods, network pruning has shown to be considerably useful in model compression by introducing sparsity or eliminating channels or filters, yet requires extensive knowledge and effort to find the perfect balance between the accuracy and model size.

The main challenge of network pruning is to find the best pruning schedule or strategy for the layers of a network. Furthermore, a pruning strategy for a given DNN cannot be used for other networks due to their different structure. Thus, each network demands a customized pruning strategy. Recently, He et al. (He et al., 2018) leveraged reinforcement learning (RL) to automatically find the best pruning strategy. However, they used manually defined rules, such as number of input/output channels, parameter size, and FLOPs for the RL environment states vectors and ignored the rich structural information within the DNN. Yu et al. (Yu et al., 2020) are the first to model a given DNN as a hierarchical graph and proposed a GNN-based encoder-decoder to embed DNN layers. However, their method learns the topology indirectly and does not consider topology changes while model compression. Moreover, existing RL-based model compression methods require manually defined pruning ratio to get the desired model size reduction. Although the model accuracy is used within the RL agent’s reward function, there is a negative correlation between the compression ratio and reward. Thus, without any constraint, the RL agent tends to search for a tiny compression ratio to get a better reward.

Deep neural networks are already being represented as computational graphs in deep-learning frameworks, such as TensorFlow (Abadi et al., 2016) and PyTorch (Paszke et al., arXiv:2102.03214v1 [cs.CV] 5 Feb 2021)
Such a representation contains various patterns (a.k.a motifs) repeated throughout the network topology. For instance, MobileNetV2 (Sandler et al., 2018) involves 17 blocks, each following a similar graph and operation structure. The topology of the blocks can represent their states, allowing us to exploit their redundancy and importance and search for a suitable compression policy. Such structural characteristics within DNNs inspired us to model them as hierarchical computational graphs and learn the compression policy.

In a nutshell, we model a given DNN as hierarchical computational graphs and propose multi-stage graph neural networks (m-GNN) to embed DNNs. Additionally, we equipped m-GNN with a reinforcement learning agent (GNN-RL) to automatically search for the compression policy (e.g., pruning ratios). To avoid tiny compression ratios due to the negative correlation between the compression ratio and RL agent’s reward, we created a DNN-Graph environment for the GNN-RL agent. Such an environment allows the agent to continuously compress the DNNs until it satisfies the model size constraint. For each step of the compression, the DNN-Graph environment converts the compressed DNN to a graph. The graph is the environment state input to the GNN-RL agent. Once the compressed DNN satisfies the desired model size, the DNN-Graph ends the search episodes and uses the pruned DNN’s accuracy as a reward for the agent.

In essence, this paper makes the following contributions:

- A novel method for modeling DNNs as hierarchical graphs to exploit their topological information for network pruning.
- An efficient multi-stage GNN and a learning-based pooling method to learn hierarchical graph embeddings.
- A topology-aware solution based on GNN and RL for automatic network pruning.
- State-of-the-art model compression results on various DNN models.

2. Related Work

Within the context of this paper, researchers already proposed various methods to compress DNN models, such as architecture design, network pruning, and quantization. Graph neural networks are also gaining momentum among these research fields. In the following, we will review these methods.

Model Compression. Extensive works focus on model compression and efficient deployment of DNNs, such as network pruning (Han et al., 2016; He et al., 2018), knowledge distillation (Hinton et al., 2015), and network quantization (Han et al., 2016; Courbariaux et al., 2016; Rastegari et al., 2016). Within the scope of this paper, we mainly consider network pruning. Structured (Anwar et al., 2017) and unstructured pruning (Zhang et al., 2018a; Guo et al., 2016) evaluate model parameters importance and remove those with a lower rank. The unstructured pruning promises a higher compression ratio by tensor sparsification. However, the potential speedup is only attainable on specialized AI-accelerators. On the other hand, structured pruning attempts to eliminate filters or channels and provides benefit to all hardware platforms. For instance, the uniform, shallow, deep empirical structured pruning policies (He et al., 2017; Li et al., 2016), the hand-crafted structured pruning methods, such as SPP (Wang et al., 2017), FP (Li et al., 2016), and RNP (Lin et al., 2017) fall into the structured pruning category. The SPP analyzes each layer and measures a reconstruction error to determine the pruning ratio. FP evaluates the performance of single-layer-pruning and ranks the importance of layers and prunes aggressively on low ranks. RNP groups all convolutional channels into sets and trains an RL agent to decide on the sets. However, hand-crafted pruning policies often fail to be extended to new models and might lead to sub-optimal performance.

Recently, researchers tend to leverage reinforcement learning to search for pruning policies automatically. Liu et al. (Liu et al., 2020) proposed an ADMM-based (Boyd et al., 2011) structured weight pruning method and an innovative additional purification step for further weight reduction. He et al. (He et al., 2018) proposed the AMC for network pruning and leveraged reinforcement learning to predict each hidden layer’s compression policies. However, they manually defined DNN’s embeddings and ignored the neural network’s essential structural information. Yu et al. (Yu et al., 2020) are the first to model DNNs as graphs and introduced a GNN-based graph encoder-decoder to embed DNNs’ hidden layers. Nevertheless, their RL agent learns the topology information indirectly and is insensitive to the structural changes of DNNs while being pruned.

Graph Neural Networks (GNN). GNN and its variants (Kipf & Welling, 2017; Schlichtkrull et al., 2018) can learn the graph embeddings and have been successfully used for link prediction (Liben-Nowell & Kleinberg, 2007) and node classification. However, these methods are mainly focused on node embedding and are inherently flat, which is inefficient to deal with the hierarchical data. In this paper, we aim to learn the global topology information from DNNs. Thus, we proposed multi-stage GNN (m-GNN), which takes advantage of the repetitive motifs available in DNNs. m-GNN considers the edge features and has a novel learning-based pooling strategy to learn the global graph embedding.
3. Approach

To prune a given DNN, the user provides the model size constraint (e.g., FLOPs-constraint). The DNN-Graph environment receives the constraint, takes the DNN’s hierarchical computational graph as the environment state, and leverages the GNN-RL agent to search for a compression policy.

Figure 1 depicts a high-level overview of our method. The DNN-Graph environment episode is essentially a model compression iteration. As the red arrows show, the process starts from the original DNN. The model size evaluator first evaluates the size of the DNN. If the size is not satisfied, the graph generator converts the DNN to a hierarchical computational graph. Then the GNN-RL agent leverages m-GNN to learn pruning ratios (compression policy) from the graph. The pruner prunes the DNN with the pruning ratios and begins the next iteration from the compressed DNN. Each step of the compression will lead to DNN’s topology change. Thus, the DNN-Graph environment reconstructs a new hierarchical computational graph for the GNN-RL agent corresponding to the current compression state.

Once the compressed DNN satisfies the size constraint, the evaluator will end the episode, and the accuracy evaluator will assess the pruned DNN’s accuracy as an episode reward for the GNN-RL agent. As opposed to the existing RL-based methods (He et al., 2018; Yu et al., 2020; Liu et al., 2020), with the DNN-Graph environment, the GNN-RL can automatically learn to reach the desired model size. Hence, it prevents us from manual adjustments and obtaining tiny compression ratios.

In the following, we will explain the details of the m-GNN and RL agent within our approach.

3.1. Hierarchical graph representation

Neural networks representation as computational graphs in deep learning frameworks, such as TensorFlow and PyTorch, contains rich topology information. However, it may involve billions of operations (He et al., 2016), which makes the computational graph bloated. Nevertheless, computational graphs often contain repetitive sub-graphs (a.k.a. motifs), such as $3 \times 3$ convolutions or custom blocks in state-of-the-art networks. We can simplify the computational graphs by extracting the motifs and modeling them as hierarchical computational graphs. Additionally, we can make the graph coarser by replacing primitive operations such as add, multiple, and minus with machine-learning high-level operations (e.g., convolution, pooling, etc.).

Formally, we model the DNN as an $l$-layer hierarchical computational graph, such that at the $i^{th}$ layer (the top layer) we would have the hierarchical computational graph set $G^l = \{G^l\}$, where each item is a computational graph $G^l = (V^l, E^l, G^{l-1})$. $V^l$ is the graph nodes corresponding to hidden states. $E^l$ is the set of directed edges with a specific edge type associated with the operations. Lastly, $G^{l-1} = \{G_0^{l-1}, G_1^{l-1}, ..., \}$ is the computational graph set at the $(l-1)$-layer and the operation set at layer $l$. Within the first layer, we manually choose commonly used machine learning operations as the primitive operations for $G^0$.

As an example, Figure 2 illustrates the idea behind generating hierarchical computational graphs using a sample graph $G$, where the edges are operations and the nodes are hidden states. In the input graph, we choose three primitive operations $G^0 = \{1 \times 1 \text{conv}, 3 \times 3 \text{conv}, 3 \times 3 \text{max-pooling}\}$ corresponding to the three edge types. Then, we extract the repetitive subgraphs (i.e., $G^1_1$, $G^1_2$ and $G^1_3$), each denoting a compound operation, and decompose the graph $G$ into two hierarchical levels, as shown in Figure 2 (b) and (c). The level-1 computational graphs are motifs that correspond to the edges within the level-2 computational graph.

The hierarchical computation graph’s size depends on the primitive operations we choose in $G^0$. In our experiments, we choose the commonly used operations in machine learning as primitive operations (e.g., convolution, pooling, etc.).
Figure 2. A two-level hierarchical computational graph and m-GNN. (a) A computational graph $G$ with motifs (the sub-graph painted red, blue, and green). The nodes on the graph denote the feature maps of input data and the edges corresponding to operations. (b) Level 1 hierarchical computational graphs. We extract motifs $\{G^1_1, G^1_2, G^1_3\}$ from $G$ and split the $G$ into 2 hierarchical levels. Level 1 are motifs. (c) Level 2 hierarchical computational graph $G^2$. The edges in $G^2$ correspond to motifs at level 1. The m-GNN embeds the 2-level hierarchical computational graph in two stages. At stage 1, m-GNN embeds the motifs $\{G^1_1, G^1_2, G^1_3\}$, and applies their embeddings (i.e., $e_1, e_2$ and $e_3$) as the edge features of $G^2$. At stage 2, the m-GNN embeds the $G^2$, and its embedding $g$ is the final embedding of the 2-level hierarchical computational graph.

3.2. Network pruning using GNN and RL

3.2.1. MULTI-STAGE GNN

Standard GNN and its variants (Kipf & Welling, 2017) are inherently flat (Ying et al., 2018). Since we model a given DNN as an $l$-layer hierarchical computational graph (see Section 3.1), we propose a multi-stage GNN (m-GNN), which embeds the hierarchical graph in $l$-stages according to its hierarchical levels and analyzes the motifs.

As depicted in Figure 2, m-GNN initially learns the lower level embeddings and uses them as the corresponding edge features in high-level computation graphs. Instead of learning node embeddings, m-GNN aims to learn the global graph representation. We further introduced a novel learning-based pooling strategy for every stage of embedding. With m-GNN, we only need embedding once for each motif on the computational graph. It is much more efficient and uses less memory than embedding a flat computation graph with standard GNN.

**Multi-stage Embedding.** For the computational graphs $G^t = \{G^t_0, G^t_1, ..., G^t_N_t\}$ in the $t^{th}$ hierarchical layer, we embed the computational graph $G^t_i = (V^t_i, E^t_i, G^{t-1})$, $i = \{1, 2, ..., N_t\}$ as:

$$e^t_i = EncoderGNN_i(G^t_i, E_{t-1}) \quad (1)$$

where $e^t_i$ is the embedding vector of $G^t_i$. $E_{t-1} = \{e^{t-1}_j\}$, $j = \{1, 2, ..., N_{t-1}\}$ is the embedding of the computational graphs at level $t-1$ and the type of edges at level $t$. For layer-1, $E_0$ contains the initial features (e.g., one-hot, and random standard) of the primitive operations $G^0$ that we manually select.

In the hierarchical computational graphs, each edge corresponds to a computational graph of the previous level and uses its graph embedding as the edge feature. Furthermore, the graphs at the same hierarchical level share the GNN’s parameter. At the top layer ($l^{th}$ layer) of the hierarchical graph $G^l = \{G^l\}$, we only have one computational graph and its embedding is the DNN’s final embedding $g$:

$$g = EncoderGNN_l(G^l, E_{l-1}) \quad (2)$$

**Message passing.** In the multi-stage hierarchical embedding, we consider the edge features. However in the standard graph convolutional networks (GCN) (Kipf & Welling, 2017), it only passes the node features and the message passing function can be formulated as follows:

$$h^{l+1}_i = \sum_{j \in N_i} \frac{1}{c_i} W^l h^l_j \quad (3)$$

where $h$ is nodes’ hidden states, $c_i$ is a constant coefficient, $N_i$ is node $i$ neighbors, and $W^l$ is GNN’s learnable weight matrix. Instead of standard message passing, in the multi-stage GNN, we add the edge features:

$$h^{l+1}_i = \sum_{j \in N_i} \frac{1}{c_i} W^l (h^l_j \circ e^{l-1}_k) \quad (4)$$

where $e^{l-1}_k$ is the features of edge $(i, j)$ and is also the embeddings of the $k^{th}$ graph at layer $l-1$, such that the edge $(i, j)$ corresponds to the operation $G^{l-1}_k$. The operation $\circ$ denotes the element-wise product, which we selected for the convenience of multi-stage message passing, but it is not limited to element-wise product.

**Learning-based pooling.** Standard GNN aims to learn the node embeddings of a graph (e.g., learn node representation and perform node classification). However, our goal is to learn the graph representation of a given DNN. Thus, we introduced a learning-based pooling method for multi-stage GNN to pool node embeddings and learn the graph embedding. We define the graph embedding $e$ as:

$$e = \sum_{i \in N} \alpha_i h_i \quad (5)$$
We employ deep deterministic policy gradient (DDPG) RL (Lillicrap et al., 2016) together with m-GNN (GNN-RL) to learn the compression policy directly from topology states. The actor and critic network within the GNN-RL agent contain an m-GNN graph encoder and a multi-layer perception. The graph encoder is used to learn the graph embedding, and the multi-layer perception projects the embedding into action space (i.e., compression policy). The actor’s output layer applies the sigmoid function to bound the actions within (0, 1).

Specifically, we perform FLOPs-constrained model compression using structured channel pruning (filter pruning) on the DNN’s convolutional layers, which are the most computationally intensive. Thus, the GNN-RL agent’s action space \( A \in \mathbb{R}^{N \times 1} \), where the \( N \) is the number of pruning layers, is the pruning ratios for hidden layers: \( A = a_i \), where \( i = \{1, 2, ..., N\} \), and \( a_i \in [0, 1) \) is the pruning ratio for \( i^{th} \) layer. The GNN-RL agent makes the actions directly from the topology states:

\[
g = \text{GraphEncoder}(G^l) \tag{6}
\]
\[
A = \text{MLP}(g) \tag{7}
\]

, where the \( G^l \) is the environment states, \( g \) is the graph representation, The MLP is a multi-layer perception neural network. The graph encoder learns the topology embedding, and the MLP projects the embedding into hidden layers’ pruning ratios. The reward function is defined in Equation 8.

\[
R_{err} = -\text{Error} \tag{8}
\]

, where the Error is the compressed DNN’s Top-1 error on validation set.

4. Experiments

To show the effectiveness of the GNN-RL, we evaluate our approach on over-parameterized DNNs (e.g., ResNet-20/32/44/56/110(He et al., 2016) and VGG-16(Simonyan & Zisserman, 2015)) and mobile-friendly DNNs (e.g., MobileNet(Howard et al., 2017; Sandler et al., 2018) and Shufflenet(Ma et al., 2018; Zhang et al., 2018b)). Additionally, to demonstrate the superiority of our proposed method, we compare GNN-RL with three sets of methods:

- Uniform, shallow, and deep empirical policies (He et al., 2017; Li et al., 2016).
- The handcrafted channel reduction methods, such as SPP(Wang et al., 2017), FP (Li et al., 2016), and RNP (Lin et al., 2017).
- The state-of-the-art RL-Based AutoML methods, such as AMC (He et al., 2018), AGMC (Yu et al., 2020), and random search (RS) with RL.

We use soft target update rate \( \tau = 0.01 \) for the GNN-RL updates. In the first 30 episodes, we warm up the agent with random action. Then exploits 150 episodes with exponentially decayed noise and trains the network with 64 batch size and 2000 as replay buffer size.

The experiment involves multiple datasets, including CIFAR-10/100 (Krizhevsky & Hinton, 2009), and ImageNet (Russakovsky et al., 2015). In the CIFAR-10/100 dataset, we sample \( 5K \) images from the test set as the validation set. In ILSVRC-2012, we split \( 10K \) images from the test set as the validation set. When searching, the DNN-Graph environment uses the compressed model’s \( R_{err} \) on the validation set as the GNN-RL agent’s reward.

4.1. Over-parameterized DNNs

We evaluate the effectiveness of GNN-RL on ResNet-20/32/44/56/110(He et al., 2016) and VGG-16 (Simonyan & Zisserman, 2015), which fall into the over-parameterized networks category. With its residual connections, ResNet avoids gradient vanishing and allows an efficient training on its deep layers. However, its deep neural structure and billions of parameters make ResNet a challenging network to deploy on edge devices. Similarly, the VGG-16 network contains compact and dense convolutional layers, where some layers have hundreds of filters, leading to a giant model size (528 MB GPU memory for VGG-16). To compress these over-parameterized DNNs, we perform FLOPs-constrained channel pruning (filter pruning) on their convolutional layers.

We trained ResNet-20/32/44/56/110 and VGG-16 models on CIFAR-10 (Krizhevsky & Hinton, 2009) and ImageNet (Russakovsky et al., 2015) datasets, respectively. Since the validation accuracy on the ImageNet dataset is sensitive to the compression ratio, with high compression ratios, the accuracy drops considerably without fine-tuning (in some cases, the pruned model without fine-tuning has...
less than 1% validation accuracy). We applied a one epoch fine-tuning process on each RL search episode to ensure that the GNN-RL gets a valuable reward when pruning the VGG-16. When pruning the ResNet-20/32/44/56/110, we share the pruning index between residual connection layers to avoid channel mismatch.

Table 1 shows the top-1 test accuracy of the pruned models. We set the 50% FLOPs constraint, and all the RL-Based methods use the $R_{err}$ as the reward. After pruning, we fine-tuned the DNNs with 100 epochs and only updated pruned layers’ parameters. Results show that GNN-RL outperforms all the baselines and achieves higher test accuracy and compression ratio. For the ResNet-110/56/44 models, the model pruned by the GNN-RL even achieves higher test accuracy than the original model. After further investigations, we believe that it is due to the over-fitting of ResNet-110/56/44, as the accuracy on the training set was 100%. To verify our assumption, we performed a further experiment to explore the relationship between the FLOPs constraints and the accuracy of DNNs. Figure 4 shows the FLOPs ratio between 0.4 to 0.6 (compared to the original model’s FLOPs) can get the highest test accuracy on ResNet-110. When the FLOPs reduction ratio exceeds 0.6, the test accuracy drops intensively.

In addition to the experiments above, we further analyzed the redundancy and the importance of each layer. Figure 3 shows the hidden layers’ pruning ratios on ResNet-110 and ResNet-56. ResNet contains residual connection layers, which transfer hidden states directly from previous residual layers. Thus, the residual connection layers are more redundant and informative since they contain the information of both the current layer’s hidden states and the previous layers. The GNN-RL agent automatically learns that the residual connection layers are more redundant and applies more pruning on the residual connection layers. Another insight from Figure 3 is that the GNN-RL agent applies more pruning on layers 45 to 65 within ResNet-110. Similarly, layers 23 to 35 of ResNet-56 have been pruned more. Such an insight shows that the middle layers have less impact on model accuracy.

4.2. Mobile-friendly DNNs

We evaluated GNN-RL on MobileNet-v1/v2 (Howard et al., 2017; Sandler et al., 2018) and ShuffleNet-v1/v2 (Zhang et al., 2018b; Ma et al., 2018), which are more suitable for devices with limited resources. Instead of using traditional convolutional operation, the MobileNet-v1/v2 and ShuffleNet-v1/v2 have designed more efficient convolutional blocks. To maintain the characteristics and high-efficiency of those custom-designed blocks, we have devel-
Table 1. Top-1 Classification accuracy for pruned over-parameterized DNNs. The original ResNet-110/56/44/32/20 are pre-trained on CIFAR-10 with Top-1 test accuracy of 93.68%, 93.39%, 93.10%, 92.63%, and 91.73%, respectively. The original VGG-16 is pre-trained on ImageNet with Top-1 test accuracy of 70.5%. The column FLOPs is the preserved FLOPs ratio compared with the original model.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>METHOD</th>
<th>FLOPS</th>
<th>Acc. (%)</th>
<th>ΔAcc. (%)</th>
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</thead>
<tbody>
<tr>
<td>ResNet110</td>
<td>AGMC</td>
<td>50%</td>
<td>93.08</td>
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<td></td>
<td>RS</td>
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<td></td>
<td>DEEP</td>
<td>50%</td>
<td>88.4</td>
<td>-4.99</td>
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<td></td>
<td>AMC</td>
<td>50%</td>
<td>90.2</td>
<td>-3.19</td>
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<td></td>
<td>AGMC</td>
<td>50%</td>
<td>92.0</td>
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<td></td>
<td>RS</td>
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<td>-1.75</td>
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Table 2. Top-1 Classification accuracies for pruned mobile-friendly DNNs. The original MobileNet-v1/v2 and ShuffleNet-v1/v2 are pre-trained on CIFAR-100 with Top-1 test accuracy of 64.88%, 65.74%, 68.64%, and 68.85%, respectively. The column FLOPs is the preserved FLOPs ratio compared with the original model.

<table>
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<th>MODEL</th>
<th>METHOD</th>
<th>FLOPS</th>
<th>Acc. (%)</th>
<th>ΔAcc. (%)</th>
</tr>
</thead>
<tbody>
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<td>AGMC</td>
<td>60%</td>
<td>65.26</td>
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<td>RS</td>
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<td>63.7</td>
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<tr>
<td>SHUFFLENet-v2</td>
<td>AGMC</td>
<td>60%</td>
<td>66.28</td>
<td>-2.57</td>
</tr>
<tr>
<td></td>
<td>RS</td>
<td>60%</td>
<td>65.74</td>
<td>-3.11</td>
</tr>
<tr>
<td></td>
<td>GNN-RL</td>
<td>54%</td>
<td>66.64</td>
<td>-2.21</td>
</tr>
<tr>
<td>MOBILENet-v1</td>
<td>AGMC</td>
<td>80%</td>
<td>64.71</td>
<td>-0.17</td>
</tr>
<tr>
<td></td>
<td>RS</td>
<td>80%</td>
<td>63.89</td>
<td>-0.99</td>
</tr>
<tr>
<td></td>
<td>GNN-RL</td>
<td>79%</td>
<td>64.79</td>
<td>-0.09</td>
</tr>
<tr>
<td>MOBILENet-v2</td>
<td>AGMC</td>
<td>80%</td>
<td>65.21</td>
<td>-0.53</td>
</tr>
<tr>
<td></td>
<td>RS</td>
<td>80%</td>
<td>65.14</td>
<td>-0.6</td>
</tr>
<tr>
<td></td>
<td>GNN-RL</td>
<td>79%</td>
<td>65.93</td>
<td>+0.19</td>
</tr>
</tbody>
</table>

opposed specific pruning strategies for them.

4.2.1. Pruning Strategy

MobileNet-v1. The MobileNet-v1 block separates the convolution into the depth-wise and point-wise convolutions (Howard et al., 2017). Each depth-wise filter only operates on one channel of feature maps. On the other hand, point-wise operations are the $1 \times 1$ convolutions, which operate on the feature maps processed by the depth-wise convolutions. In our experiments, applying regular filter pruning on such layers causes information loss. As depicted in Figure 5, pruning the filter painted in grey causes its corresponding channel (the green one) to be deleted as well. To handle this, instead of pruning depth-wise and point-wise filters separately, we only prune the point-wise filters within MobileNet-v1 blocks.

MobileNet-v2. The MobileNet-v2 is principally designed based on MobileNet-v1 blocks with an additional linear expansion layer. The linear expansion layers are $1 \times 1$ convolutions without non-linear activation. Residual shortcuts are between every two linear expansion layers, which connect MobileNet-v1 blocks. Similar to the MobileNet-v1, here we prune linear expansion layers and point-wise convolutional layers. Since residual connections are between linear expansion layers, we share the linear expansion layers’ pruning ratio.

ShuffleNet-v1/v2. The ShuffleNet model uses blocks containing depth-wise and point-wise convolutions, channel shuffle, linear expansion, and residual connections. To avoid dimension mismatch when downsampling, we consider the ShuffleNet blocks together and perform channel pruning inside the blocks. In a ShuffleNet block, we do not prune the expansion layer (the output layer of the block), which can preserve the number of output channels and keep the feature maps dimensions when downsampling.

4.2.2. Results

Table 2 shows the FLOPs-constrained channel pruning results with 60% and 80% FLOPs ratio for ShuffleNet and MobileNet, respectively. We have compared GNN-RL with AGMC (Yu et al., 2020), and random search (RS) with RL. We did not include AMC and handcrafted methods since we designed specific pruning strategies for mobile-friendly DNNs. We believe that these strategies are incompatible with AMC layer embeddings and handcrafted rules, leading to unfair comparison.

The MobileNet-v1/v2 and ShuffleNet-v1/v2 are pre-trained on the CIFAR-100 (Krizhevsky & Hinton, 2009). After pruning, we fine-tuned the compressed DNNs with 150 epochs. Our approach outperformed all the baselines. Although the networks have already been very compact, with
The VGG-16 is tested on the ImageNet, and MobileNet-v1/v2 and ShuffleNet-v1/v2 are tested on the CIFAR-100. The column FLOPs is the preserved FLOPs ratio compared with the original model.

Table 3 shows the inference accelerations and memory savings on our GPU. All the models pruned by GNN-RL achieve noteworthy inference acceleration and GPU memory reductions. Particularly, for the VGG-16, the original model’s GPU memory usage is 528 MB since it has a very compact dense layer, which contributes little to FLOPs but leads to extensive memory requirement. The GNN-RL prunes convolutional layers and significantly reduces the feature map size, thus consuming 141 MB less memory than the original version. The inference acceleration on VGG-16 is also noticeable, with 1.38× speed up on the ImageNet.

The inference acceleration for mobile-friendly DNNs may seem relatively insignificant. However, such models are designed for deployment on mobile devices. Thus, we believe that our tested GPU, with its extensive resources, does not take advantage of the mobile-friendly properties.

## 5. Conclusion

This paper proposes a network compression approach called GNN-RL, which utilizes a graph neural network and a reinforcement learning agent to exploit a topology-aware compression policy. We introduced a DNN-Graph environment that converts compression states to a topology changing process and allows GNN-RL to learn the desired compression ratio without human intervention. To efficiently embed DNNs and take advantage of motifs, we introduced m-GNN, a new multi-stage graph embedding method. In our experiments, GNN-RL is validated and verified on over-parameterized and mobile-friendly networks. For the over-parameterized models pruned by GNN-RL, ResNet-110/56/44, the test accuracy even outperformed the original models, i.e., +0.63% on ResNet-110, +0.1% on ResNet-56 and +0.13% on ResNet-44. For mobile-friendly DNNs, the 79% FLOPs MobileNet-v2 pruned by GNN-RL increased the test accuracy by 0.19% compared to the original model. Additionally, all the pruned models accelerated the inference speed and saved a considerable amount of memory usage.

## References


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