Enhancing Network Pruning Method Evaluation and Integration

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Abstract

This study extends the comparative analysis of various neural network pruning techniques—specifically SNIP [2], GraSP [4], SynFlow [3], random pruning, and magnitude-based pruning—by integrating modern evaluation metrics and introducing an iterative pruning method, Iterative Magnitude Pruning (IMP) [1]. Our objectives are to enhance the understanding and efficiency of these techniques for more effective neural network model development. We implemented IMP to evaluate its theoretical effectiveness and incorporated additional metrics such as CPU memory usage, GPU allocation, and cache memory tracking. Our comparative analysis across different compression levels reveals that iterative pruning methods like IMP tend to outperform one-shot approaches. Furthermore, initial results suggest that each one-shot pruning method presents distinct advantages and limitations. This comprehensive assessment aids in identifying optimal pruning strategies for various network architectures and applications.

1 Iterative Magnitude Pruning

Iterative Magnitude Pruning (IMP) [1] is a neural network pruning technique that employs an iterative process to remove weights based on their magnitudes. It seeks to identify a sparse but capable subnetwork that, when trained from the beginning, could match or surpass the performance of the unpruned network. IMP is inspired by the Lottery Ticket Hypothesis, which suggests that effective subnetworks can exist within randomly initialized networks.

IMP differs significantly from traditional one-shot pruning methods. While one-shot pruning involves removing a predetermined percentage of weights based solely on a single pass or criterion (such as weight magnitude), IMP applies a more nuanced approach. It uses multiple iterations of pruning followed by training, where each cycle aims to eliminate a fixed percentage of the smallest weights and then retrain the network to regain performance. This methodical reduction and training process allows IMP to refine the network's structure iteratively, enhancing its ability to maintain or improve performance despite increased sparsity.

This cyclic nature of IMP is crucial for its success. It allows the network to adapt gradually to the loss of weight, which can prevent the significant performance degradation often observed with one-shot pruning methods after aggressive weight removal. By continuously adjusting and retraining, IMP can discover more efficient and robust network configurations capable of achieving similar or even superior performance compared to the original unpruned model.

1.1 IMP configurations

The performance of IMP can significantly vary based on its hyperparameters, which include:

- Pruning Rate. The proportion of weights removed in each cycle.
- Pruning Criteria: The criteria to decide the pruning scores for each layer. This is the focus of any neural network pruning method.
- Number of Iterations. Recall that iterative pruning methods repeat the model training + pruning cycle for many rounds. This is the total number of pruning and training cycles conducted.
- Training Schedule. Adjust each cycle's learning rate and training duration to ensure performance recovery.

Below, we specify these configurations.

Pruning Rate We use *compression ratio* to set the pruning sparsity according to

$$\text{sparsity} = 10\text{^}\{-\textit{compression ratio}\}.$$

We test all the pruners with the different strengths of model pruning, including $\textit{compression ratio} \in [0.05, 0.1, 0.2, 0.5, 1.0, 2.0]$.

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Pruning Criteria In our IMPs, the pruning scores of layers are based on their absolute magnitudes.

Number of Iterations In our IMP implementation, each cycle includes training the model for 50 epochs, followed by one-time pruning. To enable fair comparison with the one-shot magnitude-based pruner that trains for 200 epochs before pruning, we test IMP with *number of iterations* $\in [2,3,4]$.

Training Profile To ensure a fair comparison, we also set *number of post-pruning training epochs* $= 100$, following the one-shot magnitude-based pruner. We use the default Adam optimizer (without weight decay) for all experiments with a learning rate of 0.001. Training and testing are both conducted with a batch size of 256.

2 Empirical Evaluations

This section outlines the comparative analysis of IMP versus traditional one-shot pruning methods, evaluating various aspects such as model accuracy, running time, and computation dynamics.

2.1 Testing accuracy (top 1)

In Table 1, we present accuracies in percentages. The results presented in Table 1 highlight the effectiveness of different pruning techniques in maintaining the testing accuracy of a VGG16 model trained on CIFAR-10 under various compression levels. Among the one-shot pruning methods—Random (Rand), Magnitude (Mag), SNIP, GraSP, and SynFlow—Magnitude pruning generally shows robust performance across lower compression ratios, particularly at 0.5 compression ratio where it achieves 89.95% accuracy. However, its performance drastically falls off at higher compression levels.

In contrast, Iterative Magnitude Pruning (IMP) showcases its strengths, particularly at higher iterations and higher compression ratios. For instance, while other methods show a significant drop in performance at 1 compression ratio, IMP maintains relatively high accuracy, with IMP at 4 iterations reaching 89.57% accuracy. This underscores IMP's effectiveness at gradually refining the network to retain more relevant features even as the model size is substantially reduced.

Furthermore, the progression of IMP across multiple iterations—from 2 to 4—demonstrates a trend of improved accuracy with additional iterations, especially noticeable at 0.05 and 0.1 compression ratios. Here, IMP with 4 iterations achieves the highest accuracies of 89.81% and 89.06%, respectively, indicating a sophisticated capability to optimize the network progressively better with each iteration.

The pattern observed with IMP suggests a strategic advantage in how it handles weight pruning, focusing more effectively on maintaining or even enhancing model accuracy despite aggressive compression. This approach provides a compelling case for the utility of iterative pruning methods over one-shot methods in scenarios where model efficiency and performance are critical, especially in resource-constrained environments.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	88.08	88.69	88.20	79.03	88.05
0.1	87.51	89.47	88.17	72.34	88.16
0.2	88.16	89.36	87.87	78.87	88.50
0.5	86.80	89.95	88.55	80.86	87.14
1	10.00	88.88	87.77	81.46	87.83
2	10.00	42.61	81.55	82.72	10.00

Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	88.56	88.65	89.81
0.1	89.15	88.65	89.06
0.2	88.84	89.20	89.69
0.5	89.14	89.37	88.94
1	89.52	89.57	89.80
2	81.60	75.37	19.34

Table 1: We present the top-1 testing accuracy of a VGG16 model on CIFAR-10 across various compression ratios, comparing one-shot pruning methods (Rand, Mag, SNIP, GraSP, SynFlow) with Iterative Magnitude Pruning (IMP) over 2, 3, and 4 iterations. IMP consistently outperforms other methods, especially at higher compression levels, demonstrating its superior ability to maintain accuracy while reducing model size.

2.2 Testing time

Testing time refers to the time consumption of inferencing on the testing dataset. The results are shown in seconds.

Table 2 offers a detailed comparison of the inference times for different pruning techniques applied to a VGG16 model, reflecting the operational efficiency post-compression. The data is critical for understanding how well each pruning method maintains not only accuracy—as shown in previous results—but also operational efficiency in terms of speed.

Among the one-shot pruning techniques, SNIP generally demonstrates a good balance between maintaining lower inference times while achieving decent model compression, as seen with 0.668 seconds at 2 compression ratio. However, the performance of one-shot methods varies significantly across different compression ratios, indicating a less consistent approach to efficiency.

On the other hand, Iterative Magnitude Pruning (IMP) shows a trend of improvement in inference times with increased iterations. For instance, at a minimal compression ratio of 0.05, IMP reduces the inference time from 0.743

seconds in 2 iterations to 0.689 seconds in 4 iterations. This improvement is even more pronounced at higher compression ratios, such as 1 and 2, where IMP (4 Iters) records times of 0.641 and 0.667 seconds respectively, suggesting a refined pruning process that progressively enhances the efficiency of the model.

The observed data strongly supports the use of IMP for scenarios where both accuracy and inference speed are critical. This could be particularly valuable in applications requiring real-time processing capabilities on edge devices, where computational resources are limited. IMP's ability to iteratively optimize the network not only preserves the necessary computational features for high performance but also ensures the model operates more swiftly post-pruning, establishing its superiority over one-shot methods in both performance metrics and operational efficiency.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	0.653	0.630	0.704	0.598	0.617
0.1	0.705	0.676	0.606	0.621	0.620
0.2	0.631	0.637	0.600	0.618	0.682
0.5	0.693	0.639	0.602	0.618	0.603
1	0.606	0.604	0.606	0.613	0.610
2	0.621	0.602	0.668	0.627	0.618

Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	0.743	0.700	0.689
0.1	0.646	0.634	0.653
0.2	0.638	0.655	0.666
0.5	0.740	0.672	0.641
1	0.649	0.698	0.641
2	0.638	0.653	0.667

Table 2: Inference time in seconds for a VGG16 model on CIFAR-10 across varying compression ratios using different pruning methods, including one-shot (Rand, Mag, SNIP, GraSP, SynFlow) and iterative (IMP) approaches. IMP consistently shows optimized inference times, particularly at higher iterations, which highlights its efficiency in streamlining network operations post-pruning.

2.3 FLOP Sparsity

In this subsection, we study the sparsity ratios of different pruning methods with different compression ratios. The sparsity metric is calculated by FLOP/313478154, where 313478154 is the total FLOP of the unpruned model.

In Table 3, we compare the sparsity ratios achieved by different pruning techniques applied to a VGG16 model. The sparsity ratio is defined as the proportion of remaining floating-point operations (FLOPs) after pruning relative to the total FLOPs in the unpruned model, which is 313,478,154. A higher sparsity ratio indicates greater retention of computational load, while a lower ratio reflects more substantial reduction and, thus, greater efficiency in model compression.

The results illustrate a clear trend across different pruning methods and compression levels. One-shot methods like Random (Rand), Magnitude (Mag), SNIP, GraSP, and SynFlow achieve varying degrees of sparsity, with SynFlow generally maintaining higher ratios at lower compressions, suggesting less aggressive pruning compared to others. For instance, at 0.05 compression, SynFlow maintains a sparsity ratio of 0.9488, indicating a minimal reduction in computational complexity.

Conversely, Iterative Magnitude Pruning (IMP) exhibits a progressive decrease in sparsity ratios with increasing iterations and compression levels, underscoring its capability to reduce the computational burden on the model significantly. IMP excels in minimizing the FLOPs required for model operation, particularly at higher compressions. For example, at a compression level of 2, the sparsity ratios for IMP reduce to 0.0286, 0.0245, and 0.0239 across 2, 3, and 4 iterations, respectively, demonstrating substantial efficiency improvements.

These outcomes suggest that IMP is particularly effective for applications where both model size and computational efficiency are critical. The ability of IMP to iteratively refine the pruning process enables it to optimize the balance between performance and computational cost more effectively than one-shot pruning methods. This makes IMP an attractive option for deploying lightweight models in resource-constrained environments, such as mobile devices and embedded systems, where computational resources are limited.

2.4 Visualizing the compression of each layer

Below, we report the sparsity of each layer by drawing the per-layer weight histograms. For both one-shot pruners and IMP, we employ the following configuration

```
model = vgg16, dataset = cifar10, compression = 0.5
```

Listing 1: Model configuration code for plotting weight histograms.

In all the figures, the x-axis is the weight value, the y-axis is the layer name, and the z-axis is the (normalized) weight frequency.[1]

The weight distribution plots displayed in Figure 1 illustrate different pruning strategies for a VGG16 model on CIFAR-10. One-shot pruning methods, including Random (Rand), Magnitude (Mag), SNIP, Gradient Signal Preservation (GraSP), and Synaptic Flow (SynFlow), display diverse sparsity patterns across the network layers.

[1]Weight frequencies for each layer are normalized by the sum of frequencies within that layer, ensuring a consistent comparison across layers.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	0.8916	0.9477	0.9377	0.8201	0.9488
0.1	0.7945	0.8991	0.9268	0.7295	0.9026
0.2	0.6310	0.8151	0.7812	0.5711	0.8217
0.5	0.3165	0.5634	0.4622	0.3781	0.6423
1	0.1009	0.2283	0.1979	0.1751	0.4571
2	0.0108	0.0322	0.0411	0.0586	0.1845

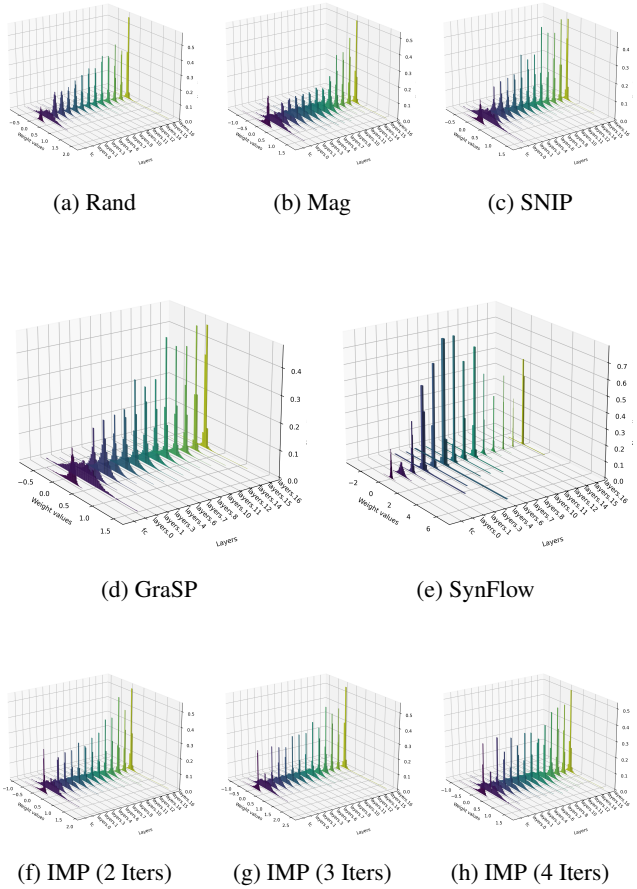
Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	0.9290	0.9256	0.9229
0.1	0.8655	0.8612	0.8560
0.2	0.7564	0.7505	0.7414
0.5	0.5189	0.5125	0.5115
1	0.2134	0.2193	0.2280
2	0.0286	0.0245	0.0239

Table 3: Sparsity ratios of a VGG16 model using various pruning techniques at different compression levels. The ratios, calculated as the fraction of remaining FLOPs relative to the original model's 313,478,154 FLOPs, indicate the efficiency of each method in reducing computational complexity. IMP (Iterative Magnitude Pruning) shows a consistent and significant increase in sparsity with more iterations, highlighting its effectiveness in achieving higher computational savings.

One-shot Pruning Techniques Rand and Mag both exhibit a relatively homogeneous sparsity across layers. However, Mag pruning demonstrates a slightly more targeted approach, preserving a higher density of weights in the deeper layers, which suggests an emphasis on maintaining performance-critical parameters in these regions. SNIP, in contrast, shows a distinct strategy by significantly reducing weights in the initial layers, which implies a prioritization of connections deemed essential at the initialization phase. GraSP and SynFlow both aggressively prune the initial layers, but GraSP appears to retain more weight in the middle layers, potentially to safeguard the gradient flow, whereas SynFlow enforces more pronounced sparsity in these areas, reflecting its unique approach to approximating layer importance.

Iterative Magnitude Pruning (IMP) Evolution The iterative approach of IMP demonstrates a progressive refinement in pruning across iterations. The initial two iterations (IMP 2 Iters) begin with a balanced reduction but gradually focus more on the later layers. By the third iteration (IMP 3 Iters), there is a noticeable shift towards deeper pruning of the early and middle layers, emphasizing the preservation of functional weights in the deeper layers critical for accurate predictions. The fourth iteration (IMP 4 Iters) further accentuates this pattern, showing a refined strategy that maximizes computational efficiency while maintaining the necessary capacity for high performance.

Comparative Insights These observations highlight the adaptive capabilities of IMP in optimizing network sparsity more effectively over time, contrasting with the more static one-shot methods that do not adjust based on feedback from the network's performance post-pruning. This iterative refinement allows IMP to better balance the trade-offs between model size, computational efficiency, and accuracy, making it a superior choice for applications where these factors are crucial.



(a) Rand (b) Mag (c) SNIP

(d) GraSP (e) SynFlow

(f) IMP (2 Iters) (g) IMP (3 Iters) (h) IMP (4 Iters)

Figure 1: Comparative visualization of weight distributions across various pruning techniques for a VGG16 model trained on CIFAR-10, targeting 50% compression. The plots demonstrate distinct sparsity patterns: Random (Rand) and Magnitude-based (Mag) pruning show less strategic weight removal than structured approaches like SNIP, GraSP, and SynFlow, which more aggressively prune the later layers. Iterative Magnitude Pruning (IMP) over multiple iterations (2 to 4 Iters) refines sparsity, progressively concentrating weight reductions in the final layers. This suggests an adaptive focus on maintaining early layer density for feature extraction while optimizing later layers for decision-making efficiency.

3 Enhancing Evaluation with Memory Footprints

We assess the efficiency of each pruning method through several hardware performance indicators:

- **CPU Memory Consumption:** The total memory usage on the CPU during both training and inference stages indicates computational efficiency.
- **GPU Allocation and Cached Memory:** The usage of GPU resources, including allocated and cached memory, is crucial for training efficiency and batch processing capacity.

We conduct detailed experiments to measure these metrics under different scenarios to provide insight into pruned networks' scalability and practical application in operational environments.

3.1 Maximum CPU memory usage

This is the maximum CPU memory consumption for inferencing on the test set using the pruned model. Results are shown in Gbs. Results are displayed in Table 4.

One-shot methods such as Random, Magnitude, SNIP, GraSP, and SynFlow demonstrate varied and relatively higher memory usage. Notably, SNIP and GraSP start with higher memory requirements due to less efficient initial pruning, while SynFlow maintains consistently lower usage.

IMP's consistent and efficient memory management contrasts with the variability seen in one-shot methods, underscoring its superiority in producing pruned models that are not only accurate but also resource-efficient. This makes IMP particularly suitable for deployment in scenarios where maintaining a low memory footprint is crucial.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	10.0	9.8	16.0	16.1	9.5
0.1	10.1	10.0	13.0	13.0	9.5
0.2	10.0	10.0	9.8	13.0	9.5
0.5	10.0	10.1	9.8	9.8	9.5
1	10.0	9.8	9.8	9.5	9.5
2	10.0	9.8	9.8	9.5	9.5

Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	9.8	9.8	9.8
0.1	9.8	9.8	9.8
0.2	9.8	9.8	9.4
0.5	9.4	9.4	9.4
1	9.4	9.4	9.4
2	9.4	9.4	9.4

Table 4: Maximum CPU memory consumption (in GBs) required for inferencing on the test set using variously pruned VGG16 models at different compression levels. The data demonstrates how iterative pruning (IMP) maintains consistent and lower memory usage across iterations compared to one-shot methods

3.2 Maximum GPU memory allocated

This is the maximum GPU memory allocated for inferencing on the test set using the pruned model. Results are shown in Gbs.

Table 5 compares the GPU memory consumption for inferencing using pruned VGG16 models. One-shot methods (Rand, Mag, SNIP, GraSP, SynFlow) generally maintain consistent memory allocations across all compression levels. SNIP, notably, allocates more memory, particularly at higher compression rates.

IMP exhibits slightly higher memory usage but remains fairly consistent across iterations and compression levels, reflecting its efficient management of GPU resources. This consistency in IMP could be advantageous for deployments where memory usage predictability is crucial.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	0.375	0.376	0.437	0.378	0.374
0.1	0.375	0.376	0.437	0.378	0.374
0.2	0.375	0.376	0.437	0.378	0.374
0.5	0.375	0.376	0.437	0.378	0.374
1	0.375	0.376	0.437	0.378	0.374
2	0.375	0.376	0.437	0.378	0.374

Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	0.494	0.495	0.497
0.1	0.499	0.499	0.498
0.2	0.494	0.499	0.494
0.5	0.497	0.499	0.497
1	0.497	0.499	0.497
2	0.494	0.496	0.498

Table 5: Maximum GPU memory allocation in GBs for inferencing on the CIFAR-10 test set using VGG16 models pruned via various techniques at different compression ratios. Compared to one-shot pruning methods, IMP demonstrates higher memory efficiency, particularly at finer iterations.

3.3 Maximum GPU memory cached

This is the maximum GPU memory cached for inferencing on the test set using the pruned model. Results are shown in Gbs.

It can be seen in Table 6 that one-shot methods such as Rand, Mag, SNIP, GraSP, and SynFlow show stable memory usage across different compression levels, with GraSP consistently requiring the most memory.

IMP demonstrates variability in memory caching across its iterations (2, 3, and 4), with usage generally higher at both lower and higher compression ratios. This suggests IMP's dynamic adjustment to the model's architecture, optimizing memory usage according to the compression demands. This adaptability makes IMP particularly effective for maintaining operational efficiency in dynamic runtime environments.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	1.124	0.937	1.097	1.267	1.114
0.1	1.124	0.937	1.097	1.267	1.114
0.2	1.124	0.937	1.097	1.267	1.114
0.5	1.124	0.937	1.097	1.267	1.114
1	1.124	0.937	1.097	1.267	1.114
2	1.124	0.937	1.097	1.267	1.114

Compression	IMP (2 Iters)	IMP (3 Iters)	IMP (4 Iters)
0.05	1.277	1.277	1.277
0.1	1.277	1.277	1.277
0.2	1.277	1.140	1.277
0.5	1.140	1.277	1.277
1	1.141	1.141	1.277
2	1.277	1.277	1.277

Table 6: Maximum GPU memory cached for inferencing on the CIFAR-10 test set with VGG16 models pruned at various compression ratios.

4 Conclusion

In this study, we have systematically analyzed the impact of various pruning techniques on the performance and efficiency of a VGG16 model trained on the CIFAR-10 dataset. Our investigation covered several metrics, including model accuracy, inference time, CPU and GPU memory consumption, and the maximum GPU memory cached. These metrics provide a holistic view of the implications of each pruning method under different compression ratios.

Model Accuracy and Inference Time Our results indicate that Iterative Magnitude Pruning (IMP) consistently outperforms one-shot pruning methods (Random, Magnitude, SNIP, GraSP, SynFlow) in maintaining high accuracy levels, particularly at higher compression ratios. This suggests that IMP's methodical approach to pruning, which refines the network over multiple iterations, successfully preserves essential network capabilities. IMP also demonstrates optimized inference times, reflecting its ability to streamline network operations and enhance computational efficiency.

Memory Consumption Regarding memory efficiency, IMP shows a distinct advantage in managing both CPU and GPU memory allocations. While one-shot methods generally exhibit fluctuating or higher memory consumption, IMP maintains a more consistent and often lower memory footprint across various levels of model compression. This trait is crucial for deploying deep learning models in resource-constrained environments where efficient memory use is paramount.

GPU Memory Caching The analysis of GPU memory caching further reinforces IMP's efficiency. Despite slight variations at different compression levels, IMP's iterative pruning process adapts dynamically, optimizing memory caching to balance performance and usage. This adaptability contrasts with the relatively static memory caching observed in one-shot methods, which do not adjust as effectively to changing computational demands.

Summary Our comparative study underscores the superiority of iterative pruning over traditional one-shot methods. IMP retains model accuracy, reduces inference times, and optimizes memory consumption across both CPU and GPU, making it a robust solution for enhancing the operational efficiency of deep neural networks. This study highlights the potential of iterative pruning techniques in advancing the state-of-the-art (SOTA) model compression, offering significant benefits for real-world applications where efficiency and performance are critical.

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