GMP★: Well-Tuned Gradual Magnitude Pruning Can Outperform Most BERT-Pruning Methods

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Abstract

We revisit the performance of the classic gradual magnitude pruning (GMP) baseline for large language models, focusing on the classic BERT benchmark on various popular tasks. Despite existing evidence in the literature that GMP performs poorly, we show that a simple and general variant, which we call GMP★, can match and sometimes outperform more complex state-of-the-art methods. Our results provide a simple yet strong baseline for future work, highlight the importance of parameter tuning for baselines, and even improve the performance of the state-of-the-art second-order pruning method in this setting.

1 Introduction

The massive recent growth of the computational cost of accurate deep learning models, in particular large language models (LLMs), has motivated the development of several advanced model compression techniques (Hoefler et al., 2021; Gholami et al., 2021), encompassing unstructured and structured pruning, quantization, and knowledge distillation. In this paper, we focus on the unstructured pruning, for which we follow the standard pipeline. Such models are first pre-trained on a large upstream corpus of unlabelled text. Then, they are fine-tuned in a supervised manner on a smaller downstream task, such as question-answering or text classification. In the context of compression, this pipeline led to two paradigms: 1) upstream pruning, followed by fine-tuning of the remaining weights on a downstream task, and 2) downstream pruning, pruning and fine-tuning directly on the downstream task.

A tempting baseline approach in most settings is gradual magnitude pruning (GMP) (Hagiwara, 1994; Zhu and Gupta, 2017), that is, periodically removing the smallest fraction of weights during training, possibly interspersed with fine-tuning steps designed to recover accuracy. GMP has been shown to be an extremely strong baseline in the context of computer vision (Gale et al., 2019; Hoefler et al., 2021). However, the literature on pruning LLMs, and in particular BERT models (Sanh et al., 2020; Chen et al., 2020; Zafrir et al., 2021), clearly suggests that GMP does not perform well.

Contribution. In this paper, we re-examine this conclusion and investigate whether GMP can be a competitive baseline, once carefully tuned. Specifically, we show that a well tuned variant which we call GMP★, can produce highly accurate and sparse language models in both upstream and downstream pruning regimes, matching or even outperforming more complex methods. We explore effects of the crucial parameters for gradual pruning, and provide simple and intuitive guidelines on how to integrate them in a principled manner.

Figure 1: Performance of state-of-the-art unstructured pruning methods relative to the dense BERT_BASE model at high sparsities and two tasks, SQuADv1.1 and MNLI.
Our results are summarized in Figure 1, which presents performance of state-of-the-art unstructured pruning techniques on two benchmarks. Specifically, we compare GMP⋆ with the Lottery Ticket approach (Chen et al., 2020), Movement Pruning (MvP) (Sanh et al., 2020) (as well as its GMP baseline GMPMvP), upstream Prune OFA (Zafrir et al., 2021), as well as the recently-proposed second-order pruning oBERT (Kurtic et al., 2022). We observe that: 1) for both benchmarks, GMP⋆ is only second to the more complex oBERT method; 2) GMP⋆ in fact outperforms the highly competitive Prune OFA and MvP methods; and 3) GMP⋆ outperforms both Lottery Tickets and GMPMvP by extremely wide margins.

Prior Work. Following the vast BERT-pruning literature, we focus on the unstructured pruning of the BERT_BASE model (Devlin et al., 2019). As previously noted, upstream and downstream pruning paradigms exist, and methods are usually developed and specialized for only one of the two. For example, Movement Pruning (MvP) (Sanh et al., 2020; Lagunas et al., 2021) for downstream pruning and Prune Once for All (Prune OFA) (Zafrir et al., 2021) for upstream pruning. Simplicity and generality of the GMP makes it suitable for both paradigms, without any regime-specific modifications. New and more advanced pruning techniques, which are, contrary to GMP, able to leverage gradients (Sanh et al., 2020; Lagunas et al., 2021), loss curvature (Kurtic et al., 2022), compute-intensive pre-training setup (Zafrir et al., 2021) are built on the premise that the simple magnitude-based GMP method falters when applied to BERT-pruning. In this work, contrary to what is currently available in the literature, we present empirical evidence that GMP, when tuned carefully, can produce very accurate sparse models which are competitive or even better than most state-of-the-art pruning techniques across both regimes (upstream and downstream). As can be seen from Figure 1 and our later results, we massively improve upon existing GMP-based pruning baselines, in some cases by even more than 20 accuracy points.

2 Competitive Gradual Magnitude Pruning (GMP⋆)

Experimental setup. We focus our attention on the standard BERT_BASE model, composed of embedding and encoder layers, which has approximately 110M parameters. All methods focus on pruning among approximately 85M weights of encoder layers and report sparsities with respect to that number. We evaluate models on the validation split of the respective dataset, and to improve confidence in the obtained results we perform multiple runs with different seeds and report mean performance.

2.1 Downstream pruning

Following the literature, we consider three popular tasks: question-answering SQuADv1.1 (Rajpurkar et al., 2016), recognition of textual entailment MNLI (Williams et al., 2017), and duplicate question detection QQP (Iyer et al., 2017). Now, we reflect upon the most important constituents of the gradual pruning framework that enabled us to attain massive improvements.

Sparsity schedule. In all of our gradual runs, there is no pruning during the first two and the last two epochs. The former fine-tunes the pre-trained model, and the latter fine-tunes the sparse model with the fixed mask. In between the two, GMP⋆ follows the cubic sparsity scheduler (Zhu and Gupta, 2017) and prunes weights with the frequency of ten times per epoch. Motivated by the fact that BERT_BASE is heavily overparametrized for downstream tasks, we deviate from the standard cubic schedule by introducing a large first pruning step. This showed to be of a crucial importance when pruning the model to high target sparsities (e.g. 97%) as it leaves more time to recover from later pruning steps which are much more difficult. In Table 8 we report results from an ablation study with respect to the size of the initial step. For convenience, we visualize the sparsity scheduler in Figure 2. Our preliminary experiments showed similar performance between uniform and global sparsity distributions, so we use the former.

Learning rate schedule. Our goal is to provide a simple baseline setup that works well across wide range of datasets without any additional task-dependent tuning. Currently, papers either report best results following an extensive hyperparameter
search for each task, e.g. Zafrir et al. (2021), or they make use of carefully crafted schedulers for each setup independently which may include warm-up phases with and without renews (Sanh et al., 2020; Kurtic et al., 2022). This may lead to high specialization to the target task/model, which is undesirable in practice and makes it hard to distinguish benefits from the pruning technique itself. We propose to simply replicate the standard 2-epoch fine-tuning schedule (Devlin et al., 2019) by a certain factor and intertwine it with pruning steps. For a fair comparison with Sanh et al. (2020) we replicate it by a factor of 5, reproducing their 10-epoch setup. And for a fair comparison with Chen et al. (2020) we replicate it by a factor of 15, reproducing their 30-epoch setup. For convenience, we visualize the learning rate schedule in Figure 2. In appendix F, we describe results with other schedulers that didn’t work.

**Knowledge Distillation (KD) Hardness.** We leverage KD (Hinton et al., 2015) of outputs from a fine-tuned dense teacher. KD is a standard practice when pruning, e.g. (Sanh et al., 2020; Zafrir et al., 2021; Xu et al., 2021). The loss function is formulated as a linear combination of the standard loss associated with the specific task (e.g. cross-entropy for classification \( L_{CE} \) and the Kullback-Leibler divergence \( L_{KL} \)) between output distributions of the dense (teacher) model and the sparse (student) model in the form: \( L = (1 - h) L_{CE} + h L_{KL} \). The ratio between the two is controlled with the hardness hyperparameter \( h \). To determine its optimal value at high sparsities we run an ablation study reported in Table 10, and adopt the hardness \( h = 1 \).

**Knowledge Distillation Temperature.** The temperature \( T \) is an additional KD-hyperparameter that requires proper tuning, as it controls the “softness” of the output distribution. In the pruning literature, it is standard to use the “stronger” \( T = 1 \) or \( T = 2 \) values (Xu et al., 2021; Zafrir et al., 2021; Sanh et al., 2020; Lagunas et al., 2021; Kurtic et al., 2022); we revisit this by visualizing teacher’s output distributions to get an insight into what the sparse student is learning. In Figure 3, we visualize generated distributions for randomly picked samples from the SQuADv1.1 task softened with three values of the temperature. As can be seen, teacher’s high confidence in predicting the correct class at the commonly used temperatures \( T \in \{1.0, 2.0\} \) makes the knowledge distillation almost obsolete. Motivated by this observation, we run an ablation study for many higher temperatures and report a fraction of results in Table 11. Given the results, we adopt the temperature \( T = 5.5 \).

### 2.1.1 GMP★ vs. other GMP-based baselines

Due to space constraints, we aggregate all the previously analyzed improvements in a downstream pruning recipe and present it in detail in Appendix B. We compare our optimized GMP★ with other GMP results reported in the pruning literature. For a fair comparison, we consider both setups, 10 and 30-epoch. In the 10-epoch setup, we compare against the GMP baselines reported in Sanh et al. (2020) and refer to them as GMP\textsubscript{MvP}. In the 30-epoch setup, we compare against the best reported results in Chen et al. (2020), obtained either via GMP or via Lottery Ticket (LTH) approach, and refer to them as GMP\textsubscript{LTH}. As can be seen from the Table 1, our GMP★ remarkably outperforms all other results; in some cases the improvements are more than 20 points!

**Table 1: Downstream pruning comparison of GMP★ with other GMP-based baselines.**

| Method     | Spars. | Ep. | SQuAD F1 | MNLI m-acc | QQP acc |
|------------|--------|-----|----------|------------|--------|
| BASE       | 0%     | 88.5| 84.5     | 91.1       |
| GMP\textsubscript{MvP} | 90%    | 10  | 80.1     | 78.3       | 79.8   |
| GMP★       | 97%    | 10  | 86.7     | 81.9       | 90.6   |
| GMP\textsubscript{MvP} | 90%    | 30  | 59.6     | 69.4       | 72.4   |
| GMP★       | 97%    | 30  | 81.3     | 79.1       | 89.7   |
| GMP\textsubscript{LTH} | 90%    | 30  | 68.0     | 75.0       | 90.0   |
| GMP★       | 97%    | 30  | 87.9     | 82.7       | 90.8   |

**Figure 3: Teacher’s output distribution at commonly used temperatures \( T \in \{1.0, 2.0\} \) and the proposed \( T = 5.5 \).**
Table 2: Downstream pruning comparison of GMP★ with advanced pruning techniques.

| Method       | Spars. | Ep. | SQuAD F1 | MNLI m-acc | QQP acc |
|--------------|--------|-----|----------|------------|--------|
| BERT BASE    | 0%     |     | 88.5     | 84.5       | 91.1   |
| GMP★         | 90%    | 10  | 86.7     | 81.9       | 90.6   |
| MVP          |        |     | 84.9     | 81.2       | 90.2   |
| GMP★         | 97%    | 10  | 81.3     | 79.1       | 89.7   |
| MVP          |        |     | 82.3     | 79.5       | 89.1   |
| GMP★         | 90%    | 30  | 87.9     | 82.7       | 90.8   |
| oBERT        |        |     | 88.3     | 83.8       | 91.4   |
| GMP★         | 97%    | 30  | 85.4     | 80.9       | 90.6   |
| oBERT        |        |     | 86.6     |            |        |

ing decisions, like gradients in MVP (Sanh et al., 2020) and the loss curvature in oBERT (Kurtic et al., 2022). Both of these impose higher computational overhead compared to the magnitude-based pruning, but we still put our results in the context with respect to theirs to fully grasp the scope of improvements introduced by careful optimizations of GMP. As can be seen from results in Table 2, GMP★ is able to improve upon the performance of Movement Pruning in 4 out of 6 analyzed configurations, but unfortunately can’t match the performance of the oBERT method. In addition to these comparisons, we make use of the open-source implementation of oBERT, current state-of-the-art BERT-pruning method, and run it with optimized hyperparameters from GMP★ on the SQuADv1.1 task. We refer to these results as oBERT★. As can be seen from the Table 2, even the very competitive oBERT results benefit from the GMP★ setup. For all GMP★ runs, we report mean performance across three runs with different seeds, and additional metrics in Tables 5 and 6.

2.2 Upstream pruning

To validate the optimized GMP★ setup introduced in the previous section, we apply it now to the pre-training phase of LLMs. This is a two-stage process. In the first stage, the BERT BASE model is pruned during pre-training and then, in the second stage, the remaining weights are fine-tuned with the fixed mask on a specific downstream task to evaluate performance. Given the high costs of experimenting in the pre-training phase, we use the dense teacher open-sourced by Kurtic et al. (2022). Due to the space constraints, we summarize all hyperparameters in an upstream pruning recipe and present it in detail in Appendix C. In Table 3 we present results obtained in this setup and compare against other methods that are utilizing the same approach. More specifically, we compare against the Lottery Ticket (Chen et al., 2020), Prune OFA (Zafrir et al., 2021), and The Optimal BERT Surgeon (oBERT) (Kurtic et al., 2022). In addition to this, we report the GMP baselines obtained in the Prune OFA work and refer to them as GMP Prune OFA. As can be seen from the Table 3, the GMP★ significantly outperforms GMP Prune OFA, Lottery Tickets and even the Prune OFA, and comes really close to the performance of oBERT. For all GMP★ runs, we report mean performance across four runs with different seeds. These results confirm findings from the previous section and establish the GMP★ as an extremely competitive baseline in all regimes.

3 Conclusion

In this work, we presented a set of updates to the standard gradual pruning setup for BERT models which enabled us to achieve very competitive results with the simple magnitude pruner. These results outperformed, by significant margins, all magnitude-based results currently available in the pruning literature which have been used as baselines for development and benchmarking of the new and more advanced pruning techniques. We hope that these new baselines will help the community to start off from a competitive set of results when compressing large language models. Moreover, our GMP★ has even outperformed some results obtained with more advanced and computationally heavier pruning techniques. At this point, we would like to strongly emphasize that these results should not be interpreted as evidence that magnitude pruning is better than other more ad-
vanced methods. Rather, they should be interpreted as evidence that their current results could significantly benefit from updates of the gradual setup presented on the GMP\textsuperscript{⋆} use-case. To support this claim, we ran the state-of-the-art oBERT pruner with the GMP\textsuperscript{⋆} setup and managed to improve its results by non-trivial margins.

4 Limitations

As any academic study, our work is not without its limitations. Following the literature, our extensive empirical studies were conducted only on the standard BERT\textsubscript{BASE} model, giving us opportunity to compare against a vast amount of different pruning techniques. Throughout the literature, this model emerged as a consistent benchmark for unstructured pruning methods. However, the current results don’t directly imply that our findings will be generally applicable to other language models as well. To partially fill in this uncertainty gap, we conduct a few experiments on the three times larger BERT\textsubscript{LARGE} model and report results in the Appendix A. Another limitation which we aim to remove in future work is the focus on fine-grained unstructured sparsity type, and explore other variants such as semi-structured and structured pruning.

References

Tianlong Chen, Jonathan Frankle, Shiyu Chang, Sijia Liu, Yang Zhang, Zhangyang Wang, and Michael Carbin. 2020. The lottery ticket hypothesis for pre-trained bert networks. Advances in neural information processing systems, 33:15834–15846.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In North American Chapter of the Association for Computational Linguistics (NAACL).

Trevor Gale, Erich Elsen, and Sara Hooker. 2019. The state of sparsity in deep neural networks. In International Conference on Machine Learning (ICML).

Amir Gholami, Sehoon Kim, Zhen Dong, Zhexwei Yao, Michael W Mahoney, and Kurt Keutzer. 2021. A survey of quantization methods for efficient neural network inference. arXiv preprint arXiv:2103.13630.

Masafumi Hagiwara. 1994. A simple and effective method for removal of hidden units and weights. Neurocomputing, 6(2):207 – 218. Backpropagation, Part IV.

Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. 2015. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2(7).

Torsten Hoefler, Dan Alistarh, Tal Ben-Nun, Nikoli Dryden, and Alexandra Peste. 2021. Sparsity in deep learning: Pruning and growth for efficient inference and training in neural networks. arXiv preprint arXiv:2102.00554.

Shankar Iyer, Nikhil Dandekar, Kornél Csernai, et al. 2017. First quora dataset release: Question pairs. data.quora.com.

Eldar Kurtic, Daniel Campos, Tuan Nguyen, Elias Frantar, Mark Kurtz, Benjamin Fineman, Michael Goin, and Dan Alistarh. 2022. The optimal bert surgeon: Scalable and accurate second-order pruning for large language models. arXiv preprint arXiv:2203.07259.

Mark Kurtz, Justin Kopinsky, Rati Gelashvili, Alexander Matveev, John Carr, Michael Goin, William Leiserson, Sage Moore, Bill Nell, Nir Shavit, and Dan Alistarh. 2020. Inducing and exploiting activation sparsity for fast inference on deep neural networks. In International Conference on Machine Learning (ICML).

François Lagunas, Ella Charlaix, Victor Sanh, and Alexander Rush. 2021. Block pruning for faster transformers. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 10619–10629. Association for Computational Linguistics.

Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, Joe Davison, Mario Šaško, Gunjan Chhablani, Bhavitya Malik, Simon Brandeis, Teven Le Scao, Victor Sanh, Canwen Xu, Nicolas Patry, Angelina McMillan-Major, Philipp Schmid, Sylvain Gugger, Clément Delangue, Théo Matussière, Lysandre Début, Stas Bekman, Pierrick Cistac, Thibault Goehringer, Victor Mustar, François Lagunas, Alexander Rush, and Thomas Wolf. 2021. Datasets: A community library for natural language processing. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 175–184, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In Conference on Empirical Methods in Natural Language Processing (EMNLP).

Victor Sanh, Thomas Wolf, and Alexander Rush. 2020. Movement pruning: Adaptive sparsity by fine-tuning. Advances in Neural Information Processing Systems, 33:20378–20389.
B Downstream pruning recipe

All of our implementations are built on top of HuggingFace’s Transformers $^1$ (Wolf et al., 2020) and Datasets $^2$ (Lhoest et al., 2021) libraries, and NeuralMagic’s SparseML $^3$ (Kurtz et al., 2020) library for model compression, and will be open-sourced to community along with our sparse models.

As our goal is to provide a simple and unique gradual pruning setup, all of our downstream runs (for all datasets) are using the same set of hyper-parameters. The ones used to obtain results reported in Tables 1, 2, 5, and 6 are as follows:

- **learning-rate**: recurring 2-epoch scheduler (visualized in Figure 2) with the initial value of $1e^{-4}$, and the final value of $1e^{-6}$,
- **number-of-epochs**: 10 or 30 epochs, depending on the methods we compare against,
- **sparsity**: cubic scheduler with the initial pruning step of 70% sparsity (visualized in Figure 2),
- **pruning**: prune frequency of ten times per epoch, except during the first and last 2-epochs when only fine-tuning happens and masks are fixed,
- **student-initialization**: standard BERT$_{\text{BASE}}$ (bert-base-uncased$^4$),
- **knowledge-distillation (KD)**: (hardness, temperature) = (1.0, 5.5),
- **KD-teachers**: standard BERT$_{\text{BASE}}$ fine-tuned on the corresponding task,
- **weight-decay**: 0.0,
- all other hyper-parameters are set to the standard default values, e.g. Sanh et al. (2020):
  - SQuADv1.1: batch-size=16, max-sequence-length=384, doc-stride=128,
  - MNLI and QQP: batch-size=32, max-sequence-length=128.

A Additional models

All of our experiments in the paper focus on the BERT$_{\text{BASE}}$ model as it is the standard benchmark used in the pruning literature and we are able to compare results with a vast amount of other techniques. To verify that our proposed GMP$^\star$ setup doesn’t pertain only to the BERT$_{\text{BASE}}$ model, in the Table 4 we present results on the three larger BERT$_{\text{LARGE}}$ model. As a proof of concept, we run our downstream gradual pruning setup crafted for the BERT$_{\text{BASE}}$ model without any hyper-parameter tuning.

Table 4: Downstream pruning results when pruning the BERT$_{\text{LARGE}}$ model with the GMP$^\star$ and gradual setup crafted for the BERT$_{\text{BASE}}$ model.

| Method      | Sparsity | SQuAD F1 | EM  |
|-------------|----------|----------|-----|
| BERT$_{\text{LARGE}}$ | 0%       | 91.22    | 84.45 |
| GMP$^\star$ | 90%      | 90.12    | 83.21 |
| GMP$^\star$ | 97%      | 87.93    | 80.50 |

$^1$https://github.com/huggingface/transformers
$^2$https://github.com/huggingface/datasets
$^3$https://github.com/neuralmagic/sparseml
$^4$https://huggingface.co/bert-base-uncased
C Upstream pruning recipe

For a fair comparison with Zafrir et al. (2021) and Kurtic et al. (2022), we adopt the same gradual setup for pruning and fine-tuning, but apply our specific GMP⋆ updates. The entire process is carried out in two stages. The first stage prunes the BERTBASE model at upstream datasets, BookCorpus and English Wikipedia. Both datasets are available via Lhoest et al. (2021). The upstream pruning recipe can be summarized as follows:

- learning-rate: recurring 0.5-epoch scheduler with the initial learning rate value of 5e-4, and the final value of 5e-6,
- number-of-epochs: 3,
- sparsity: cubic scheduler with the initial pruning step of 70% sparsity,
- pruning: prune frequency of hundred times per epoch, except during the last epoch when only fine-tuning happens and masks are fixed,
- knowledge-distillation (KD): (hardness, temperature) = (1.0, 5.5),
- KD teacher and student initialization: BERTBASE prepared and open-sourced by Kurtic et al. (2022),
- weight-decay: 0.01,
- batch-size: 256,
- max-sequence-length: 512.

The second stage makes use of this upstream pruned model and fine-tunes it on a specific downstream task (SQuADv1.1, MNLI, QQP) for 8-epochs with fixed masks. All task-specific hyperparameters (batch-size, max-sequence-length, doc-stride, weight-decay) are the same as in Appendix B, and the remaining ones are as follows:

- learning-rate: linear decay with initial value of 1.5e-5,
- knowledge-distillation: (hardness, temperature) = (1.0, 5.5),
- KD-teachers: standard BERTBASE fine-tuned on the corresponding task.

D Additional metrics

Due to space constraints, for corresponding runs in Tables 1, 2, and 3, we present additional perfor-
Table 8: Initial sparsity step ablation study on the SQuADv1.1 dataset.

| Initial sparsity (%) | F1 score at 90% | F1 score at 97% |
|----------------------|-----------------|-----------------|
| 0                    | 85.2            | 77.2            |
| 30                   | 85.5            | 77.8            |
| 50                   | **85.8**        | **78.5**        |
| 70                   | 85.8            | **79.1**        |

Table 9: Initial learning rate ablation study on the MNLI dataset.

| Initial learning rate | Accuracy at 90% | Accuracy at 97% |
|-----------------------|-----------------|-----------------|
| 3e-5                  | 80.8            | 76.3            |
| 5e-5                  | 81.4            | 77.8            |
| 8e-5                  | **81.9**        | 78.6            |
| 1e-4                  | 81.6            | **79.3**        |

Table 10: Knowledge Distillation (KD) hardness ablation study on the SQuADv1.1 dataset.

| Knowledge distillation hardness | F1 score at 90% | F1 score at 97% |
|---------------------------------|-----------------|-----------------|
| 0.6                             | 84.6            | 78.4            |
| 0.8                             | 85.9            | 80.1            |
| 0.9                             | 86.2            | 80.7            |
| 1.0                             | **86.7**        | **81.0**        |

Table 11: Knowledge Distillation (KD) temperature ablation study on the SQuADv1.1 dataset.

| Knowledge distillation temperature | F1 score at 90% | F1 score at 97% |
|-----------------------------------|-----------------|-----------------|
| 1.0                               | 84.7            | 77.3            |
| 2.0                               | 85.8            | 79.0            |
| 5.5                               | **86.7**        | **81.0**        |
| 8.5                               | 86.4            | 80.9            |

mance metrics in Tables 5, 6, and 7.

E Ablation studies

In Tables 8, 9, 10, 11 we present a subset of results from ablation studies conducted to find the optimal values of hyperparameters for the GMP *gradual pruning setup. These results illustrate the general trend of effects caused by varying one hyperparameter. Therefore, they don’t cover all possible scenarios (i.e. higher-order effects when multiple hyperparameters are updated together), but such studies are computationally too expensive and we don’t conduct them.

F Learning rate schedulers we tried, but didn’t work

The schedulers we tried but didn’t work: 1) linearly decaying learning rate, 2) the default fine-tuning learning rates (3e-5 for SQuADv1.1 and 2e-5 for MNLI and QQP), 3) learning rates with the warm-up phase. In the preliminary experiments, we have noticed that 1) and 2) have problems in recovering from the pruning steps at higher sparsities. The former one has extremely small learning rate values during the last few epochs when the model is pruned to high sparsities. The latter one continuously fails to recover properly even at moderate sparsity targets, which is why we run a sweep over a range of initial learning rate values. Given the results in Table 9, we decided to proceed with the 1e-4 as it helped to recover significantly at high sparsities. We haven’t observed any benefits from the warmup phase, which is why we have decided not to use it as it adds an additional hyperparameter to tune.