Greedy Layer Pruning: Decreasing Inference Time of Transformer Models

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Abstract

Fine-tuning transformer models after unsupervised pre-training reaches a very high performance on many different NLP tasks. Unfortunately, transformers suffer from long inference times which greatly increases costs in production and is a limiting factor for the deployment into embedded devices. One possible solution is to use knowledge distillation, which solves this problem by transferring information from large teacher models to smaller student models, but as it needs an additional expensive pre-training phase, this solution is computationally expensive and can be financially prohibitive for smaller academic research groups. Another solution is to use layer-wise pruning methods, which reach high compression rates for transformer models and avoids the computational load of the pre-training distillation stage. The price to pay is that the performance of layer-wise pruning algorithms is not on par with state-of-the-art knowledge distillation methods. In this paper, greedy layer pruning (GLP) is introduced to (1) outperform current state-of-the-art for layer-wise pruning (2) close the performance gap when compared to knowledge distillation, while (3) using only a modest budget. More precisely, with the methodology presented it is possible to prune and evaluate competitive models on the whole GLUE benchmark with a budget of just $300. Our source code is available on GitHub

1 Introduction

Fine-tuning transformer models after unsupervised pre-training is the de-facto standard in Natural Language Processing (NLP) due to its outstanding performance on a wide range of tasks \[4, 10, 14, 16, 27, 33\]. Classical transformer models, such as BERT\[4\], are massive networks with up to 24 layers, each containing fully connected layers as well as many attention heads, which comprises more than 100M parameters as a result. This extremely large number of parameters leads to long inference times and an increase in cost if deployed in production after training. Additionally, increased memory consumption and inference-time hinder the deployment of transformer models on edge- or embedded devices. Different areas of research address this problem by targeting a reduction in memory consumption as well as inference time \[11, 13, 22, 23, 26, 30\]. One such research direction is knowledge distillation, where information is transferred from large teacher models to much smaller student models, while maintaining up to 96.8% of the performance of the teacher \[13\]. In the first step

https://github.com/deepopinion/greedy-layer-pruning

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of knowledge distillation, information is transferred during a pre-training stage from large teacher models to smaller student models. Specialized teacher models can be pre-trained additionally for better performance \[26\]. Task-agnostic knowledge distillation models such as DistilBERT \[23\] or MobileBERT \[26\] can directly be fine-tuned on downstream tasks after the pre-training distillation stage. Other models, such as TinyBERT, are computationally more expensive as they use the teacher also in the fine-tuning stage. In either of those methodologies, knowledge must be distilled from large teacher models into smaller student models during the pre-training phase to produce a compressed model. This pre-training stage can be prohibitively expensive especially for smaller academic research groups or startups which limits research and development of such compressed models to only a few well-funded industry labs \[12\]. In this work, we will introduce a method to compress and train models on a downstream task that is competitive with state-of-the-art distillation methods w.r.t memory consumption, inference time and performance, while at the same time can be executed in a modest-budget setup.

Our approach avoids the computationally expensive distillation stage from the teacher into the student by directly reducing the size of already pre-trained base models through pruning. Michel et al. \[18\], Voita et al. \[28\] and Zhang et al. \[35\] have already shown that many attention heads can be removed without a significant impact on performance. Unfortunately, the speed-up reached by those methods is not much bigger than $1.3 \times$ because only parts of the encoder layers are pruned, making them not sufficiently competitive w.r.t inference time against distilled models (fig. 1a). Much higher compression rates can be achieved through layer-wise pruning as complete encoder layers are removed from the model. Fan et al. \[6\] proposes a form of structured dropout, called LayerDrop, which is used during pre-training and fine-tuning to make models robust against removing whole layers. This solution requires an additional pre-training phase that is quite expensive to compute, especially when our goal is to keep the overall cost low. Sajjad et al. \[22\] studied many different layer-wise pruning approaches for transformers that directly operate on pre-trained models. They found that the performance is best if their top-layer pruning algorithm is used. Models that are compressed with top-layer pruning are already on-par with DistilBERT, but still behind the novel distillation methods such as TinyBERT or MobileBERT. Our goal is therefore to outperform current state-of-the-art methods (fig. 1a) for layer-wise pruning in order to reduce the performance gap when compared against distilled models (fig. 1a). This goal is quite a challenging one as, if we compare the current state of the art on GLUE for distillation with MobileBERT, it reaches a score of 81.0, while state-of-the-art layer-wise pruning reaches a score of just 79.6, which may be the reason why layer-wise pruning has been somewhat neglected until now.

We propose Greedy layer-wise pruning (GLP), an algorithm that compresses and trains transformer models while needing only a modest budget. With this algorithm, we outperform state-of-the-art layer-wise pruning algorithms providing a performance on GLUE that is comparable to most distillation methods (fig. 1). An additional advantage of GLP over distillation methods is that the compression rate can be selected by the user to reach a desired performance/compression ratio. Some of the compressed models that GLP produces even outperform the baseline as we will show in our experimental evaluation. Our experimental results also indicate that our GLP algorithm is empirically effective for different transformer models as while pruning 50% of the layers, we still maintain 95.7% of the performance of a BERT model and 94.9% of the performance of a RoBERTa model. Therefore, we will conclude that the performance of models compressed with GLP increases directly as the research on pre-trained models improves, which is another advantage over distillation, as no additional pre-training stage with a new teacher-model is necessary.

The contributions of this paper are:

- A Greedy layer-wise pruning (GLP) algorithm which is able to maintain the high performance of models while only needing a modest budget computer setup to execute.
- We experimentally show that GLP outperforms the state of the art in terms of layer-wise pruning and closes the performance gap to distillation methods such as TinyBERT or MobileBERT, and in certain cases, the compressed model also outperforms its uncompressed version.
- We compare GLP and top-layer pruning with the optimal solution (for small-problem sizes) in order to motivate and guide future research in the direction of layer-wise pruning.

This paper is structured as follows: In the next section, we define our setup and the modest budget to execute GLP. In section 3 layer-wise pruning is defined and greedy layer-wise pruning (GLP)
is introduced. In the experimental section we compare GLP against the state of the art for layer-wise pruning and for distillation, finally comparing it against the optimal solution. Related work is presented in section followed by a section that includes future work and a discussion on GLP’s limitations.

2 Problem Setup

256 TPUv3 chips are necessary only to pre-train the special teacher model IB-BERT\textsubscript{LARGE}, needed for the pre-training distillation stage of MobileBert. Our goal in this work is to compress and train a model using only a modest budget on a given downstream task while still reaching state-of-the-art performance, even when comparing against methodologies which require massive computational resources for training. Considering previous studies on modest budget setups, we define a modest budget as follows: Compress and train a model on a single downstream task of GLUE in less than 24h on average, using a single Nvidia RTX 3090 GPU. We used QNLI as a reference to measure the 24h time limit since the dataset size of QNLI is approximately the average dataset size of GLUE. In addition, it is worth mentioning that our GLP algorithm scales linearly with the number of GPUs as will be shown later. Therefore, a setup with e.g. 8 GPUs and 3h runtime is considered to be equivalent to a single GPU and 24h runtime. In the cloud, a roughly equivalent configuration would be an Nvidia Tesla P100 GPU, that costs just $32 per task, so that the execution of all 9 tasks of the GLUE benchmark would sum up to approximately $300\footnote{Pricing from \url{https://cloud.google.com/compute/gpus-pricing}. Accessed 05/05/2021}.

3 Methods

The layer-wise pruning task and the optimization problem that pruning algorithms should solve is defined as follows: Assume that a transformer model of depth $d$ consists of layers $L$ with $|L| = d$. The layer $L_0$ is the input layer and layer $L_{d-1}$ is the layer just before the classifier. Our goal is to develop an algorithm $A(L, T, n)$ for a given fine-tuning task $T$ (e.g. QNLI) that returns a subset $R_n \subseteq L$ with $|R_n| = n$. We call an algorithm $A$ task-independent if it returns the same solution $R_n$ for all tasks $T$ and task-dependent otherwise. The returned subset $R_n$ contains the layers that should be pruned from the model. Therefore, the goal of $A$ is to find a subset $R_n$ of size $n$, so that the transformer model with layers $L \setminus R_n$ maximizes some – previously specified – performance measure $M(L \setminus R_n, T)$ after being fine-tuned on the task $T$. The most used layer-wise pruning algorithm is Top-Layer Pruning. Sajjad et al. \cite{Sajjad2021} tested many different task-independent as well as task-dependent pruning algorithms and found that top-layer pruning, which prunes the last layers first, works best across many different tasks and models:

$$\text{Top}(L, T, n) = \{L_d, L_{d-1}, \ldots, L_{d-(n-1)}\}$$ (1)

Creating an algorithm $\text{Opt}(L, T, n)$ that finds the optimal solution for layer-wise pruning is easy if resources are not constrained. More precisely, from all possible combinations to prune $n$ layers, we simply select the combination of layers that produces the highest performance:

$$\text{Opt}(L, T, n) = \arg\max_{R_n} \{R_n \in \mathcal{P}_n(L) \mid M(L \setminus R_n, T)\}$$ (2)

where $\mathcal{P}(L)$ denote the set of all subsets of $L$ and $\mathcal{P}_n(L) = \{X \in \mathcal{P}(L) \mid |X| = n\}$. The computational complexity of this algorithm is therefore $O(d^n)$.

For example, to prune two layers of a BERT model with 12 layers, 66 different networks must be evaluated. We show later that at least six layers must be pruned from models like BERT\textsubscript{base} or RoBERTa\textsubscript{base} to be competitive w.r.t memory consumption and inference time against state-of-the-art distillation methods. Pruning six layers already leads to 924 different configurations that must be evaluated. For the whole GLUE benchmark, this would take almost half a year using the proposed setup.

\footnote{Sajjad et al. \cite{Sajjad2021} already showed that layer-wise pruning methods work best if executed directly after the pre-training, something we could confirm in our experiments.}
3.1 Greedy Layer Pruning (GLP)

To reduce the complexity of the optimal solution, we exploit a greedy approach \cite{3}. Greedy algorithms make a locally-optimal choice in the hope that this leads to a globally-optimum. For example to prune \( n + 1 \) layers only a single (locally-optimal) layer to prune must be added to the already known solution for pruning \( n \) layers. This statement would lead to the following assumption about layer-wise pruning:

**Assumption 3.1 (Locality).** If the set \( R_n \ (R_0 = \emptyset) \) is the optimal solution w.r.t. the performance metric \( M(L \setminus R_n, T) \) for pruning \( n \) layers on a given task \( T \) and model with layers \( L \), then \( R_n \subset R_{n+1} \).

The correctness of this assumption will be evaluated in an experimental study (section 4.4). Assuming locality, the search space and therefore the computational complexity is greatly reduced:

\[
\text{GLP}(L, T, n) = R_n = \begin{cases} 
\text{Opt}(L, T, 1) & \text{if } n = 1 \\
\text{Opt} (L \setminus R_{n-1}, T, 1) \cup R_{n-1} & \text{otherwise}
\end{cases}
\]

(3)

It can be seen that \( R_n \) can be calculated by adding the best local solution \( \text{Opt} (L \setminus R_{n-1}, T, 1) \) to the set \( R_{n-1} \) using the locality assumption \cite{3}. This simplification reduces the complexity from \( O(d_n) \) to \( O(n \times d) \). This algorithm can easily be distributed on multiple GPUs, e.g., if \( d \) GPUs are available, the algorithm can be executed in just \( n \) steps.

Our goal is to compress and train models with layer-wise pruning so that they become competitive against state-of-the-art distillation methods while using a modest budget. To get a similar speedup with pruning as with distilled models, the depth of a BERT model must be reduced to only 6 layers (fig. 1). We empirically found that in order to obtain the final 6 layers, pruning 18 layers from large models with 24 layers resulted in much lower performance than pruning 6 layers from base models with 12 layers. Therefore, our starting point for pruning will be a base model with \( d = 12 \) for the rest of the paper. To prune such a model with GLP, only 57 steps are necessary. With the proposed setup, GLP can therefore be executed in only 19h on a single Nvidia RTX 3090 GPU on QNLI, and therefore agrees with our budget constraint (section 2).

4 Experimental evaluation

We provide first results on the GLUE benchmark, comparing GLP to top-layer pruning and different distillation methods. Next, we will evaluate the validity of the main components of GLP, the locality assumption \cite{3} and the performance metric, \( M \).

4.1 Setup

**Implementation** Each experiment is executed on a node with one Nvidia RTX 3090 GPU, an Intel Core i7-10700K CPU and 128GB of memory following the description in section 2. Our publicly available implementation extends the BERT model as well as the RoBERTa model of the Transformer v.4.3.2 library (PyTorch 1.7.1 \cite{19}) from HuggingFace \cite{32} with top-layer pruning as well as greedy-layer pruning. The run_glue.py script from Huggingface is used to evaluate the GLUE benchmark. The source code also provides scripts to easily setup and reproduce all experiments.

**Evaluation** For evaluation, the GLUE benchmark \cite{29} is used, which consists of CoLA \cite{30}, SST-2 \cite{25}, MRPC \cite{5}, STS-B \cite{2}, QQP \cite{4}, MNLI \cite{31}, QNLI \cite{21}, WNLI \cite{15}, and RTE \cite{11}.

Even though in the WNLI dataset we outperformed competing pruning algorithms (e.g. GLP \( 2 \) reached 54.9% for pruning BERT on WNLI whereas Top \( 2 \) reached only 29.6%), we will exclude it in our comparison as it has been neglected in previous studies \cite{4,13,26}. In order not to overfit on a certain seed, we report the median of five runs using different seeds \cite{23} for all our experiments. Standard deviation values for table \cite{1} are not included due to space limitations, but can be consulted in the

\[https://huggingface.co/transformers/v2.5.0/examples.html#glue\]
\[https://data.quora.com/First-Quora-Dataset-Release-Question-Pairs\]
Pruning $n$ layers of RoBERTa with GLP (GLP-$n$).

Pruning $n$ layers of a BERT model with GLP (ours) and top layer pruning [22].

Figure 1: Performance on the GLUE dataset (except for WNLI) using different models w.r.t its speedup relative to BERT. The dashed line shows how the speedup and performance changes as a different number of layers are pruned with GLP. For a fair model evaluation and comparison, please note that TinyBert* uses the teacher model in the fine-tuning stage whereas all other models directly train on the downstream task [26].

supplementary material. We report the following classical evaluation metrics [29]: the F1-score for MRPC and QQP, the spearman correlation for STSB, the mathews-correlation for COLA and the accuracy for all other datasets. To ensure that our scores are not the result of any undesired side-effect or implementation details, we also executed experiments on top-layer pruning and all task-agnostic distillation methods using exactly the same code-base. As TinyBERT, as well as LayerDrop, require a special pre-training phase, we report the values reported in the original papers for these methods.

Hyperparameters We follow the hyperparameter setup from Devlin et al. [4] and use a batch size of 32 and fine-tune the base model for 3 epochs on the data for all GLUE tasks with a sequence length of 128 to evaluate all baseline models and pruned models. AdamW [17] is used as an optimizer with a learning rate of 2e-5, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 1e-8$. The same hyperparameters are also used to train DistilBERT. For training MobileBERT, we followed Sun et al. [26] and increased the learning rate to 7e-5. To ensure reproducability of our results, we not only publish the source code together with the paper, but we also provide a guild file (guild.yml) which contains the detailed hyperparameter setup we used for each experiment and which should help to replicate our experiments.

4.2 Results on GLUE

The results on GLUE for the baseline BERT and RoBERTa, as well as models pruned with top-layer and GLP pruning for 2, 4 and 6 layers are shown in table 1 and fig. 1. GLP outperforms top-layer pruning on GLUE in almost all the cases evaluated, namely for pruning BERT, and for pruning 2 and 6 layers of RoBERTa. Only in one case (pruning 4-layers from RoBERTa) top-layer pruning outperforms GLP. Pruning 6-layer is particularly important to reach a similar inference-time than distillation methods. In this case, GLP always outperforms top-layer pruning, sometimes by a large margin: Pruning 6 layers from a BERT model the difference in performance of GLP vs top-layer is 0.8 and 0.7 percentage points for RoBERTa. When compared against LayerDrop – which is a fairly expensive approach because it must be executed during both pre-training and finetuning – GLP outperforms or reaches similar scores. Please note that we could only include the partial results on GLUE reported by Fan et al. [6].

On some tasks, GLP and top-layer pruning perform equally well. For example, when pruning 2 layers from BERT on CoLA, the score is exactly the same. As an interesting point, we found that in this case, GLP prunes the same layer than top-layer pruning, but in most of the other cases, solutions are quite different, which indicates that the optimization-problem (section 3) is not task-
Table 1: Median of five runs evaluated for GLP, Top-Layer pruning and state-of-the-art task-agnostic distillation methods. The subscript $n$ indicates how many layers are pruned from the given architecture. Additional results as well as standard deviation values of all five runs can be consulted in the supplementary material. *denotes that the values are from Fan et al. [6].

| Method          | SST-2 | MNLI | QNLI | QQP | STS-B | RTE | MRPC | CoLA | GLUE |
|-----------------|-------|------|------|-----|-------|-----|------|------|------|
| GLUE            |       |      |      |     |       |     |      |      |      |
| Baseline$_0$    | 92.8  | 84.7 | 91.5 | 88.0| 88.1  | 64.6| 88.7 | 56.5 | 81.9 |
| Top$_2$         | 92.3  | 83.9 | 89.8 | 87.4| 88.0  | 64.3| 87.1 | 57.0 | 81.2 |
| GLP$_2$ (ours)  | 92.3  | 83.7 | 91.0 | 87.6| 87.9  | 65.3| 88.3 | 57.0 | 81.6 |
| Top$_4$         | 91.5  | 83.0 | 89.1 | 87.1| 88.0  | 64.3| 86.9 | 49.2 | 79.9 |
| GLP$_4$ (ours)  | 92.1  | 82.8 | 90.2 | 87.1| 87.6  | 65.3| 86.5 | 53.9 | 80.7 |
| Top$_6$         | 90.8  | 81.1 | 87.4 | 86.7| 87.7  | 63.5| 86.1 | 37.1 | 77.6 |
| GLP$_6$ (ours)  | 91.2  | 81.3 | 87.6 | 86.8| 87.6  | 61.4| 86.1 | 45.5 | 78.4 |
| Layer Pruning BERT |       |      |      |     |       |     |      |      |      |
| Baseline$_0$    |       |      |      |     |       |     |      |      |      |
| Top$_2$         | 99.7  | 87.8 | 92.9 | 88.4| 90.0  | 73.6| 92.1 | 57.5 | 84.6 |
| GLP$_2$ (ours)  | 93.7  | 87.7 | 92.8 | 88.4| 89.9  | 69.7| 90.9 | 58.1 | 83.9 |
| Top$_4$         | 93.6  | 87.2 | 92.4 | 88.3| 89.4  | 67.9| 91.3 | 54.2 | 83.0 |
| GLP$_4$ (ours)  | 93.6  | 87.2 | 92.2 | 88.2| 89.1  | 67.9| 90.3 | 54.2 | 82.8 |
| Top$_6$         | 92.5  | 84.7 | 90.9 | 87.6| 88.3  | 58.1| 88.3 | 46.6 | 79.6 |
| GLP$_6$ (ours)  | 92.0  | 85.6 | 90.8 | 87.8| 86.6  | 62.5| 88.0 | 48.8 | 80.3 |
| LayerDrop$_6$   | 92.5  | 82.9 | 89.4 | -   | -     | 85.3| -    | -    | -    |
| Layer Pruning RoBERTa |     |      |      |     |       |     |      |      |      |
| Baseline$_0$    |       |      |      |     |       |     |      |      |      |
| Top$_2$         | 99.7  | 87.8 | 92.9 | 88.4| 90.0  | 73.6| 92.1 | 57.5 | 84.6 |
| GLP$_2$ (ours)  | 93.7  | 87.7 | 92.8 | 88.4| 89.9  | 69.7| 90.9 | 58.1 | 83.9 |
| Top$_4$         | 93.6  | 87.2 | 92.4 | 88.3| 89.4  | 67.9| 91.3 | 54.2 | 83.0 |
| GLP$_4$ (ours)  | 93.6  | 87.2 | 92.2 | 88.2| 89.1  | 67.9| 90.3 | 54.2 | 82.8 |
| Top$_6$         | 92.5  | 84.7 | 90.9 | 87.6| 88.3  | 58.1| 88.3 | 46.6 | 79.6 |
| GLP$_6$ (ours)  | 92.0  | 85.6 | 90.8 | 87.8| 86.6  | 62.5| 88.0 | 48.8 | 80.3 |
| LayerDrop$_6$   | 92.5  | 82.9 | 89.4 | -   | -     | 85.3| -    | -    | -    |
| Task-agnostic Distillation |     |      |      |     |       |     |      |      |      |
| DistilBERT      | 90.1  | 82.3 | 88.8 | 86.6| 86.3  | 60.6| 88.9 | 49.4 | 79.1 |
| MobileBERT      | 91.9  | 84.0 | 91.0 | 87.5| 87.9  | 64.6| 90.6 | 50.5 | 81.0 |

Table 2: Comparison of the performance efficiency on GLUE for different layer-wise pruning executions w.r.t to its baseline. Values are computed as the performance (of GLP or Top-layer pruning) over the performance of its baseline.

| Model          | Layers | GLP (Ours) | Top |
|----------------|--------|------------|-----|
| BERT           | 2      | 99.6       | 99.1|
|                | 4      | 98.5       | 97.5|
|                | 6      | 95.7       | 94.7|
| RoBERTa        | 2      | 99.7       | 99.2|
|                | 4      | 97.8       | 98.1|
|                | 6      | 94.9       | 94.0|

In table 2, we show how much performance can be lost due to pruning $n$ layers compared to its baseline (no pruning). The performance of GLP w.r.t the baseline is in almost all cases higher than top-layer pruning. We believe that one major reason is that our algorithm selects layers based on the given task i.e. is task-dependent whereas top-layer pruning is task-independent. It can also be seen that GLP reaches a high efficiency on different models, which strongly indicates that this pruning algorithm can also be used for models that will be released in the future so that even better results can be achieved by simply applying GLP to those pre-trained models. It is worth mentioning that the performance-efficiency in terms of compression can be larger than 100% for some datasets. For example, when using GLP to prune 2 layers, the resulting model trained on RTE is not only faster and smaller, but also outperforms the baseline.
Table 3: Comparison of base models, state-of-the-art layer-wise pruning and distillation models w.r.t inference time, memory consumption and performance on GLUE. * denotes that this compression method uses a teacher model in the fine-tuning stage whereas all other models directly train on the downstream task [26]

| Method                        | Model       | GLUE  | Params. | Inference [s] | CPU | GPU |
|-------------------------------|-------------|-------|---------|---------------|-----|-----|
| Base                          | BERT        | 81.9  | 108M    | 141           | 3.0 |     |
|                               | RoBERTa     | 84.6  | 125M    | 149           | 3.0 |     |
| Task-agnostic distillation    | DistilBERT  | 79.1  | 67M     | 81            | 1.7 |     |
|                               | MobileBERT  | 81.0  | 25M     | 91            | 9.1 |     |
| Non task-agnostic distillation| TinyBERT₁₀ | 79.4  | 67M     | 74            | 1.7 |     |
| Layer-wise pruning            | LayerDrop₆₆ | -     | 82M     | 70            | 1.7 |     |
|                               | BERT+TOP₆₆ | 77.6  | 67M     | 73            | 1.7 |     |
|                               | BERT+GLP₆₆ (ours) | 78.4 | 67M     | 73            | 1.7 |     |
|                               | RoBERTa+TOP₆₆ | 79.6 | 82M     | 70            | 1.7 |     |
|                               | RoBERTa+GLP₆₆ (ours) | 80.3 | 82M     | 70            | 1.7 |     |

4.3 Distillation vs. Layer Pruning

Memory consumption, inference time, and performance on GLUE for baseline models, distillation models, and pruning methods are shown in table 3. No GLUE scores were reported for LayerDrop in Fan et al. [6]. Performance and speedup values relative to BERT are also shown in fig. [1]. To measure the inference time, we evaluated each model on the same hardware, using the same frameworks with a batch-size of 1 and perform the evaluation on a CPU [23]. Additionally, for each method we report the GPU timings, measured on an RTX 3090 GPU with a batch size of 32.

In terms of inference-time and performance (fig. [1a]), GLP is indeed on-par when compared to distillation methods. Additionally, pruning allows for balancing the speed-up/performance trade-off by changing the number of layers that should be pruned from the model (dashed line in fig. [1]). In terms of memory consumption and performance, GLP is very close to DistilBERT and TinyBERT, but the winner here is MobileBERT, which outperforms all methods. MobileBERT was introduced especially for mobile devices and so is extremely parameter efficient as it is a thin and deep architecture. On the other hand, inference of MobileBERT is slow on GPUs because parallelism on GPUs can be barely exploited with such architecture. Nevertheless, this aspect shows the limitation of layer-wise pruning in that the width is fixed and only the depth of a network can be changed, more insights on this will be discussed in section [6].

4.4 Evaluating the Locality Assumption 3.1

In this subsection we evaluate the two main components of GLP, namely, the effect of the locality assumption [3.1] and the influence of the performance metric M on the results.

We assess first if a locally optimal choice also leads to a globally optimal solution (assumption [3.1]) by evaluating all of the possible two-layer combinations pruning from a transformer model. The best results of such analysis is shown as Optimal in fig. [2] next to GLP and Top-layer pruning. If assumption [3.1] were to be correct, GLP should find a solution with the same validation error for each dataset and model. Results for the optimal solution (Optimal in fig. [2]) are computed on a fixed seed as it is important to use the same seed in order to properly evaluate if the solutions for GLP and optimal are exactly the same. In all other experiments we used multiple runs with different seeds and report the median to exclude outliers and to ensure that GLP does not depend on a single seed.

Figure [2] shows that solutions found by GLP almost always outperform top-layer pruning by a large margin, which indicates the robustness of task-dependent algorithms. The exception in this case is for RoBERTa on STS-B, where the solution found with GLP is slightly worse than top-layer pruning. GLP can find the optimal solution in many cases, for example, when applied to BERT (fig. [2a]), that is the case for SST-2, RTE, STS-B and CoLA. In others, even though GLP does not provide such optimal solution it is a close one (such as QQP, MRPC and QNLI for BERT).
the same evaluation for RoBERTa. This detailed analysis proves that the locality assumption is a good approximation, but is not fully correct. Even so, the assumption is useful because it reduces the size of the search space while keeping costs within the budget-constraint as defined in section 2. The usefulness of assumption 3.1 is confirmed in fig. 2 where we show that GLP can indeed find the global optimum in certain cases and it outperforms top-pruning by a large margin, providing comparable results to distillation methods.

Finally, we can also evaluate the choice for the performance metric $M$ used by the GLP algorithm (eq. (3)) to find locally-optimal solutions. More precisely, we replaced $M$ with the validation loss and pruned layers that produce the lowest loss value. We found in our experiments that this setup worsened the overall performance of GLP on the GLUE benchmark. For example, for pruning a BERT model, the score is worsened on average by 0.7 percentage points. Detailed results for all datasets on GLUE for RoBERTa and BERT is presented in the supplementary material.

5 Related Work

This work falls into the research area of compressing transformer architectures. Different areas of research address the problem to reduce memory consumption as well as inference time of transformer models. A comprehensive case-study on this topic is given by Ganesh et al. [7] who categorize this area into data quantization [11, 24, 34], knowledge distillation [13, 23, 26, 36], and pruning. Our work falls into the latter and can be further divided into element-wise and structured pruning. Element-wise pruning locates the set of least important weights to create sparse model representations [8, 9]. Our focus to reach high compression rates lies on structured pruning, which reduce and simplify numerical components of models to speed up the inference time. The following structural pruning methods have been already topic of investigation:
**Attention head pruning**  The contribution made by individual attention heads in the encoder has been extensively studied. Michel et al. [18] demonstrated that 16 attention-heads can be pruned down to one attention head, achieving an inference speedup of up to 17.5% if the batch size is large. Another method to prune unnecessary attention heads is through single-shot meta-pruning [35], where pruning 50% of the attention heads, reaches a speedup of about $1.3 \times$ on BERT, which is still not enough to be competitive against distilled models.

**Encoder unit pruning**  Instead of pruning only attention heads, it is also possible to prune layers of the encoder unit including all attention heads and the feedforward layer. Fan et al. [6] pre-trains BERT models with random layer dropping such that pruning becomes more robust during the fine-tuning stage. On the other hand, Sajjad et al. [22] claims that this approach is (1) expensive because it requires a pre-training from scratch of each model and (2) it is possible to outperform this methodology by dropping top-layers before fine-tuning a model. Sajjad et al. [22] evaluated six different encoder unit pruning strategies, namely, top-layer dropping, even alternate dropping, odd alternate dropping, symmetric dropping, bottom-layer dropping and contribution-based dropping. They found that (1) top-layer pruning consistently works best, (2) layers should be dropped directly after pre-training and (3) that an iterative pruning of layers does not improve the performance. Nevertheless, the proposed method and together with the task-independent top-layer pruning is not on par with distillation methods, something we addressed in this paper.

### 6 Discussion and Conclusions

In this paper, greedy layer pruning (GLP) is introduced to compress transformer models while keeping a very high performance using only a modest budget ($\$300$ to evaluate GLUE in the cloud). Our focus is on pruning methods as the pre-training stage of distillation methods is computationally expensive. The GLP algorithm presented here implements a greedy approach maintaining very high performance while needing only a modest budget computational setup. This is empirically evaluated in section 4 by comparing GLP against top-layer pruning [22], LayerDrop [6], DistilBERT [23], TinyBERT [13] and MobileBERT [26] on the GLUE benchmark. An interesting result is that GLP sometimes improved the performance of its baseline (table 1) although it is a smaller and faster model. This could be the result of certain layers that worsen the accuracy of the network [20], neural architecture search (NAS) algorithms could solve this problem and GLP may act in a similar way to NAS algorithms since performance decreasing layers are pruned first. We finally evaluated the validity of assumption 3.1 that leads to the deployment of the GLP algorithm.

Some limitations of the proposed methodology include that GLP changes only the depth of networks by pruning layers from transformer models, but it is not possible to reduce the width of models to further compress models. Additionally, GLP is task-dependent and therefore pruning must be executed with the task-specific dataset. Finally, for very deep networks with more than 50 layers (such as CNNs) the proposed greedy strategy becomes computationally expensive, and more optimization strategies (section 7) would be needed.

### 7 Future Work

We have shown that the locality assumption 3.1 is a good strategy to find comparable solutions to expensive distillation systems, but with the advantage of doing so when only limited computational resources are available. Nevertheless, there is much room for improvement as shown in our experimental evaluation (fig. 2). One interesting direction to further improve the performance could be to evaluate other different methodologies than the ones presented in the greedy approach. We report in the supplementary material a few other heuristics which unfortunately did not improve the performance. Secondly, the performance metric $\mathcal{M}$ used by GLP for evaluation could be a topic for further research. For example, Izsak et al. [12] rejects training candidates already after a few training steps if a given threshold is not reached. A similar approach for GLP could be a topic of interest to speed up the compression stage and decrease computational costs even further.
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