Depth as a Scaling Vector: Simple Pruning and Evaluation of Emergent Abilities in Pruned LLMs

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Abstract

The evolving lifecycle of large language models (LLMs) calls for effective strategies for scaling them down for deployment without sacrificing core capabilities. In this work, we investigate depth as a primary architectural scaling vector, introducing simple methods for pruning layers of LLMs, and systematically evaluate how such scaling affects the emergent abilities of LLMs. Our evaluations demonstrate that these methods offer a practical path to facilitate LLM deployment, significantly reducing computational demands while retaining the emergent abilities that make these models powerful and attractive in a wide range of applications.

1 Introduction

The widespread success of large language models (LLMs) has introduced new challenges throughout their evolving lifecycle, from initial training to widespread deployment. One primary bottleneck is caused by the immense computational and memory footprints of LLMs, which limit their accessibility and practicality in resource-constrained environments, when performance is also critical.

Strategically removing groups of parameters, pruning has emerged as a key method to address this challenge [1]. Much of the early focus was on width pruning, which removes redundant weights or neurons within layers [2, 3]. More recently, depth pruning – the removal of entire layers – has been explored as a promising alternative that can offer hardware-agnostic acceleration [4, 5, 6]. However, previous work rarely prunes LLMs to less than 50% of their original sizes and lacks systematic and unified evaluations of the emergent abilities of the pruned model in complex reasoning tasks.

In this paper, we investigate whether simple, direct depth pruning methods can preserve emergent abilities even under aggressive compression rates, where fewer than half of the layers are retained. Our contributions are threefold: (1) We introduce simple, problem-space-agnostic depth pruning methods to scale down LLMs for deployment. (2) We perform a systematic and unified evaluation to determine how the emergent abilities crucial for complex reasoning are affected by aggressive architectural compression using a wide range of state-of-the-art pruning strategies. (3) We demonstrate that these simple pruning methods can preserve key emergent capabilities even at high model sparsities, offering a practical pathway to scale down LLMs for effective deployment. We open-source our code in `https://github.com/ChangLiu-DrPatient/SimpleDepthPruning`.

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39th Conference on Neural Information Processing Systems (NeurIPS 2025) Workshop: Evaluating the Evolving LLM Lifecycle: Benchmarks, Emergent Abilities, and Scaling.

2 Related work

Model pruning offers a practical strategy for scaling LLMs down for deployment. Early attempts focus on width pruning, which sparsifies LLMs by removing weights within layers. For example, `Wanda` [2] removes weights with the smallest magnitudes multiplied by their corresponding input activations. `SparseGPT` [3] prunes LLMs one-shot and treats pruning as a large-scale sparse regression problem. More recently, depth pruning presents an alternative scaling vector by removing entire layers, effectively providing more uniform and hardware-agnostic acceleration. `ShortGPT` [4] selects layers based on layer importance scores that measure the similarity between each layer's input and output. `Shortened Llama` [5] removes layers based on the influence of each layer on the model output perplexity on a set of calibration examples. `LaCo` [6] reduces the size of the model by merging multiple subsequent layers into a single preceding layer, adding the parameter differences of the later layers to the earlier one in an iterative process guided by output similarity. However, these methods have been evaluated on different sets of benchmarks, which hinders direct comparison. Our work proposes simpler alternatives to these pruning methods and provides a systematic evaluation of how such pruning affects the emergent abilities that define modern LLMs.

3 Quite simple depth pruning methods

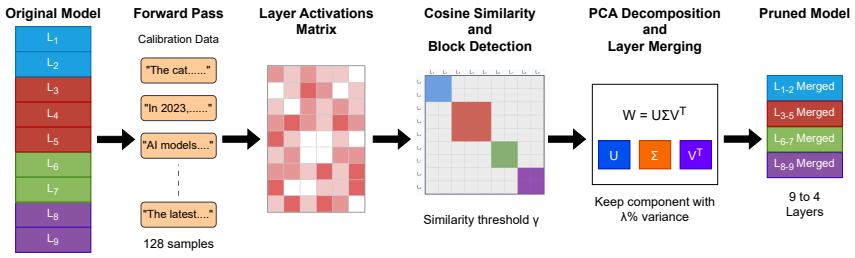

Figure 1: Overview of our `LayerMergeAct` depth pruning method.

We introduce simple depth pruning methods that effectively scale down model sizes to facilitate deployment. In all our methods, we only modify the decoder layers of an LLM, keeping the other components (e.g., embedding layers) intact. Specifically, with $\{L_1, L_2, \cdots, L_m\}$ being the original LLM decoder layers, we output a pruned model with decoder layers $\{\tilde{L}_1, \tilde{L}_2, \cdots, \tilde{L}_n\}$ where $n < m$. For aggressive pruning, we focus on cases where $n \leq \frac{m}{2}$. Note that we may carry out the pruning algorithm on a subset of layers $\{L_a, L_{a+1}, \cdots, L_b\}$ where $[a, b] \subseteq [1, m]$, and inherit the layers $\{\tilde{L}_1, \cdots, \tilde{L}_{a-1}\}$ and $\{\tilde{L}_{b+1}, \cdots, \tilde{L}_m\}$ if either of them is non-empty.

In addition, for all our methods, we determine the output decoder layers based on the parameters of a fixed module type of the original decoder layers. The set of module types include T =['self_attn.k_proj', 'self_attn.v_proj', 'self_attn.q_proj', 'self_attn.o_proj', 'mlp.gate_proj', 'mlp.up_proj', 'mlp.down_proj', 'input_layernorm', 'post_attention_layernorm']. We denote the parameters of module type $t \in T$ in layer L_i by W_i^t.

`LayerCluster`: layer selection via k-medoids clustering. For a selected range $[a, b]$ and module type t, we perform k-medoids clustering on the parameters $[W_a^t, W_{a+1}^t, \cdots, W_b^t]$, yielding k cluster centers that correspond to the indices $\{j_1, \cdots, j_k\} \subseteq \{a, a+1, \cdots, b\}$. The resulting pruned model will sequentially inherit layers $\{L_1, \cdots, L_{a-1}, L_{j_1}, \cdots, L_{j_k}, L_{b+1}, \cdots, L_m\}$ of the original model.

`LayerMerge`: layer merging via Principal Component Analysis. For a selected range $[a, b]$ and each module type t, we perform Principal Component Analysis (PCA) on the stacked parameters $[W_a^t, W_{a+1}^t, \cdots, W_b^t]$. We pick the first k principal components for each module type to form k layers $\tilde{L}_{j_1}, \cdots, \tilde{L}_{j_k}$ that replace the original set of layers, where the parameters of each module type for $\tilde{L}_{j_r}$ correspond to the r-th principal component. The resulting pruned model will consist sequentially of layers $\{L_1, \cdots, L_{a-1}, \tilde{L}_{j_1}, \cdots, \tilde{L}_{j_k}, L_{b+1}, \cdots, L_m\}$.

`LayerMergeAct`: layer merging via adaptive grouping and PCA. Unlike the previous methods, which prune the LLM based solely on its parameters, `LayerMergeAct` leverages a small set of calibration examples $\mathcal{D}$ (128 random samples from the C4 dataset [7] training split, ODC-By license). As shown in Figure 1, for each example $x \in \mathcal{D}$, we perform a single forward pass through the original LLM and record the output activations of each layer $\{z_1^x, z_2^x, \cdots, z_m^x\}$. We then compute the cosine similarity between each pair of outputs (z_i^x, z_j^x) and organize them into a cosine similarity matrix $S(x)$. We then average the similarity matrix across all samples in $\mathcal{D}$ to obtain the aggregated similarity matrix $S = \frac{1}{|\mathcal{D}|}\sum_{x\in\mathcal{D}} S(x)$. Using a user-defined threshold γ, we recursively find diagonal blocks of S where (i) all values are above γ and (ii) the minimum value in the block is largest across all available blocks that satisfy (i). More details can be found in Algorithm 1 in the Appendix.

After retrieving the block indices $\mathcal{I} = \{(s_1, e_1), (s_2, e_2), \cdots, (s_r, e_r)\}$, we perform the `LayerMerge` algorithm described in Section 3 for each pair of block indices in $\mathcal{I}$. Note that we slightly modify the algorithm by adding a global hyperparameter λ, where we keep the principal components that retain $\lambda\%$ variance for each pair of block indices instead of keeping a fixed number of principal components. The hyperparameters γ and λ determine the sparsity of the pruned LLM.

4 Experiments

To evaluate how scaling down LLMs along their depth affects key emergent abilities, we utilize the `Open LLM Leaderboard v2` (implemented in the Language Model Evaluation Harness [8], MIT license), which evaluates reasoning abilities in multiple aspects, including *mathematics and logic*, *multistep soft reasoning*, *natural language understanding*, and *graduate level domain knowledge*, etc. To facilitate rapid evaluation, we curate `Leaderboard-Lite`, a subset of 15 `Open LLM Leaderboard v2` challenges (Table 3) with the highest variance in performance when running the `LayerMergeAct` pruning algorithm under 4 different configurations that yield 50% sparsity on the `llama-2-7b-hf` base model (i.e., reduced to half of its original depth).

We compare our simple pruning methods with more complex state-of-the-art width pruning (`Wanda` [2] and `SparseGPT` [3]) and depth pruning methods (`ShortGPT` [4], `Shortened Llama` [5], and `LaCo` [6]) using `llama-2-7b-hf` and `llama-3.1-8b` as base models and a single NVIDIA Tesla V100-SXM2-32GB GPU.

Accuracy / Sparsity / Method	0.5 k=16	0.53 k=15	0.5625 k=14	0.625 k=12	0.7188 k=9	0.7813 k=7	0.8438 k=5	0.9062 k=3
`Wanda`	0.3126	0.3098	0.3101	**0.3091**	**0.3173**	**0.3121**	0.2751	0.3088
`SparseGPT`	**0.3195**	**0.3205**	**0.3155**	0.3036	0.2974	0.2907	**0.3019**	**0.3101**
`ShortGPT`	<u>0.2920</u>	0.3029	**0.3118**	**0.3088**	**0.3064**	0.2922	0.2949	<u>0.2999</u>
`Shortened Llama`	**0.2967**	0.2994	0.2915	<u>0.3014</u>	0.2793	0.2915	<u>0.3105</u>	<u>0.2999</u>
`LaCo`	0.2900	<u>0.3061</u>	<u>0.3108</u>	0.2997	<u>0.3004</u>	0.2850	0.2888	0.2798
`LayerCluster`	0.2793	0.2907	0.2689	0.2843	0.2870	0.2728	0.2822	0.2711
`LayerMerge`	0.2768	0.2793	0.2810	0.2885	0.2987	**0.3073**	**0.3113**	0.2967
`LayerMergeAct`	0.2897	**0.3091**	0.2987	<u>0.3014</u>	0.2999	<u>0.2924</u>	0.2987	**0.3062**

Table 1: The performance of pruning methods on `Leaderboard-Lite` with different LLM sparsity, using `llama-2-7b-hf` as the base model (accuracy 0.3152). "k" denotes the number of decoder layers of the depth-pruned model corresponding to the given sparsity. For each listed sparsity, the performance of the best-performing depth pruning method is marked in **bold** while the second-best is <u>underlined</u>. The best-performing width pruning method is also marked in **bold**.

Accuracy / Sparsity / Method	0.5 k=16	0.53 k=15	0.5625 k=14	0.625 k=12	0.7188 k=9	0.7813 k=7	0.8438 k=5	0.9062 k=3
`Wanda`	0.3158	0.3168	**0.3203**	**0.3185**	0.3029	**0.3021**	**0.3143**	0.2843
`SparseGPT`	**0.3277**	**0.3230**	0.3061	0.3106	**0.3051**	0.2964	0.2987	**0.3131**
`ShortGPT`	0.2838	<u>0.2992</u>	<u>0.2982</u>	**0.3091**	0.2934	**0.3049**	0.2894	**0.3004**
`Shortened Llama`	0.2927	0.2937	0.2885	0.2758	0.2920	0.2833	<u>0.2919</u>	**0.3004**
`LaCo`	<u>0.3041</u>	0.2982	**0.3071**	<u>0.3021</u>	<u>0.2969</u>	<u>0.2967</u>	0.2885	0.2862
`LayerCluster`	0.2880	**0.2994**	0.2867	0.2880	0.2751	0.2860	0.2537	0.2602
`LayerMerge`	0.2835	0.2820	0.2817	0.2830	0.2872	0.2865	0.2897	<u>0.2984</u>
`LayerMergeAct`	**0.3071**	0.2574	0.2897	0.2731	**0.3054**	0.2922	**0.2974**	0.2825

Table 2: The performance of pruning methods on `Leaderboard-Lite` with different sparsity of the pruned LLM, using `llama-3.1-8b` as the base model, which achieves an accuracy of 0.3850.

As shown in Tables 1 and 2, although simpler, our pruning methods achieve comparable and sometimes superior `Leaderboard-Lite` performance to the baselines: In particular, for the `llama-2-7b-hf` base model, our methods secured the first place among all depth pruning methods on the three largest sparsities (k = 3, 5, 7) and achieved performance comparable to that of the base model. However, for both base models, the performance of depth pruning methods generally lags behind that of width pruning methods.

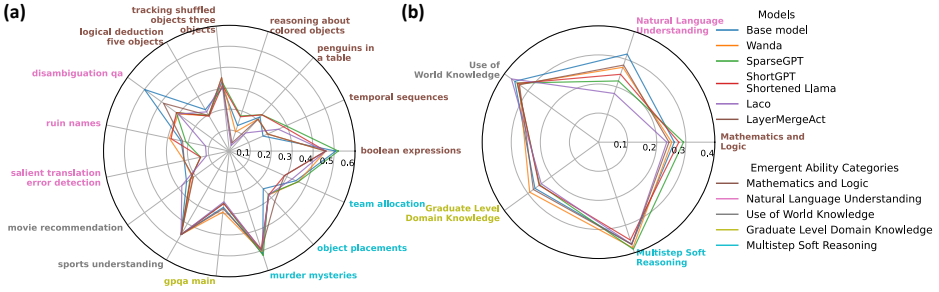

Figure 2: The performance of different pruning methods on `Leaderboard-Lite` (`llama-2-7b-hf` as the base model) with the largest model sparsity (k=3). **(a)** presents task-wise performance while **(b)** aggregates task performance by their corresponding category of emergent abilities. The layer selection methods `ShortGPT` and `Shortened Llama` resulted in identical models.

We then examine how different emergent abilities are affected when we aggressively scale down the model depth to only 3 layers. We first find that pruning strategies affect emergent abilities differently (Figure 2): While both width pruning methods outperform the depth pruning methods and the base model on *multistep soft reasoning*, `Wanda` excels in *graduate level domain knowledge* and `SparseGPT` leads in *mathematics and logic*. For depth pruning, layer selection methods (`Shortgpt` and `Shortened Llama`) slightly outperform the base model in terms of *mathematics and logic*. On the other hand, our layer merging approach `LayerMergeAct`, achieving the best overall `Leaderboard-Lite` performance (Table 1) among depth pruning methods, is the most successful in retaining emergent abilities in *graduate level domain knowledge* and *multistep soft reasoning*. Lastly, while all methods incur a noticeable drop in *natural language understanding* abilities, with the largest loss in the 'disambiguation qa' challenge, `LayerMergeAct` is the most successful in retaining this emergent ability.

We also find that there is no significant trend between depth and how well each emergent ability is retained (Figure 3). For `LayerMergeAct`, a depth of 3 layers achieves superior or comparable performance to all deeper configurations, suggesting that aggressively scaling down depth to the extreme can be viable for deployment with both resource and performance requirements.

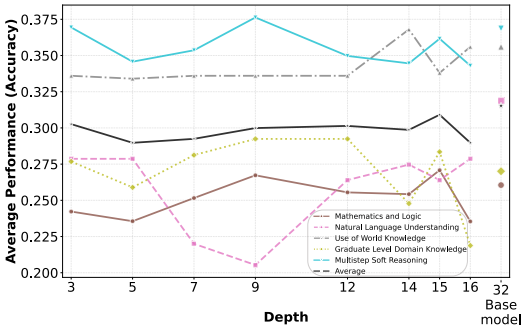

Figure 3: Emergent abilities of `LayerMergeAct`-pruned models with different depth (using `llama-2-7b-hf`).

5 Discussion

In this paper, we presented simple and direct pruning methods that reduce LLM complexities for deployment and conducted a unified and systematic evaluation of state-of-the-art pruning methods. Our evaluation showed that our methods, while aggressively shrinking the size of the model, can effectively retain key emergent abilities that empower LLMs, suggesting a practical pathway for managing the deployment of LLMs and their evolving lifecycle in general.

Although our methods achieve comparable or superior performance to the baselines, all methods suffer from a larger gap from the base model when using `llama-3.1-8b` (Table 2), while the performance of the pruned model under the same sparsity does not improve. This suggests that `llama-3.1-8b` may be less "prunable" than `llama-2-7b-hf`. As more advanced LLMs are being developed, it is interesting that they may be harder to scale down for deployment.

Furthermore, while all the evaluated methods lack a trend between performance and depth retention beyond 50% pruning (Tables 1 and 2, Figure 3), this phenomenon may also be due to the fact that task-agnostic pruning methods may be unable to retain specific emerging capabilities. In future work, we will develop targeted, task-specific methods for scaling down LLMs and expect to gain more compression at a lower loss of performance. We will also develop more systematic benchmarks that evaluate emergent abilities at finer resolutions to carefully guide the development of such methods.

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A Algorithm for finding diagonal blocks

Algorithm 1 Recursive Block Finder

Input:
Raw similarity matrix $S \in \mathbb{R}^{n \times n}$
Binarized matrix M where $M_{ij} = 1$ if $S_{ij} \geq \gamma$ and 0 otherwise, for a threshold γ.
Output:
A list of non-overlapping block indices $\mathcal{I} = [(s_1, e_1), (s_2, e_2), \dots]$

```
procedure FINDBLOCKS(S, M)
    n ← number of rows in M
    if n = 0 then return []
    end if
    if n = 1 then return [(0, 0)]
    end if
    B ← []                                   ▷ List to store potential blocks and their scores
    for s ← 0 to n − 1 do
        if M[s, s] = 1 then
            e ← s + 1
            while e < n and submatrix M[s : e, s : e] is all ones do
                e ← e + 1
            end while
            s_min ← min(S[s : e − 1, s : e − 1])
            Append ((s, e − 1), s_min) to B
        end if
    end for
    Sort B descending by block size (e − s), then by s_min
    (s*, e*) ← indices of the first block in sorted list B
    M_before ← M[0 : s* − 1, 0 : s* − 1]
    M_after ← M[e* + 1 : n − 1, e* + 1 : n − 1]
    I_before ← FindBlocks(S, M_before)
    I_after ← FindBlocks(S, M_after)
    Shift all indices (i_s, i_e) in I_after by e* + 1
    return I_before ∪ [(s*, e*)] ∪ I_after
end procedure
```

B Challenges in `Leaderboard-Lite`

Domain	Challenge
Mathematics and Logic	leaderboard_bbh_boolean_expressions leaderboard_bbh_temporal_sequences leaderboard_bbh_penguins_in_a_table leaderboard_bbh_reasoning_about_colored_objects leaderboard_bbh_tracking_shuffled_objects_three_objects leaderboard_bbh_logical_deduction_five_objects
Natural Language Understanding	leaderboard_bbh_disambiguation_qa leaderboard_bbh_ruin_names leaderboard_bbh_salient_translation_error_detection
Use of World Knowledge	leaderboard_bbh_movie_recommendation leaderboard_bbh_sports_understanding
Graduate Level Domain Knowledge	leaderboard_gpqa_main
Multistep Soft Reasoning	leaderboard_musr_murder_mysteries leaderboard_musr_object_placements leaderboard_musr_team_allocation

Table 3: Challenges in Leaderboard-Lite grouped by the measured emergent ability of the LLM.

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   Justification: They accurately reflect the paper's contributions and scope, i.e., providing simple depth pruning methods and evaluating the emergent abilities of pruned LLMs

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