

LLM Pruning and Distillation in Practice: The Minitron Approach

Sharath Turuvekere Sreenivas*, Saurav Muralidharan*, Raviraj Joshi, Marcin Chochowski, Mostofa Patwary, Mohammad Shoeybi, Bryan Catanzaro, Jan Kautz and Pavlo Molchanov

Abstract: We present a comprehensive report on compressing the Llama 3.1 8B and Mistral NeMo 12B models to 4B and 8B parameters, respectively, using pruning and distillation [1]. We explore two distinct pruning strategies: (1) depth pruning and (2) joint hidden/attention/MLP (width) pruning, and evaluate the results on common benchmarks from the LM Evaluation Harness [2]. The models are then aligned with NeMo Aligner and tested in instruct-tuned versions. This approach produces a compelling 4B model from Llama 3.1 8B and a state-of-the-art Mistral-NeMo-Minitron-8B (MN-Minitron-8B for brevity) model from Mistral NeMo 12B. We found that with no access to the original data, it is beneficial to slightly fine-tune teacher models on the distillation dataset. We open-source our base model weights on Hugging Face with a permissive license.

Models on Hugging Face: Mistral-NeMo-Minitron-8B-Base | Llama-3.1-Minitron-4B-Width-Base | Llama-3.1-Minitron-4B-Depth-Base

Introduction

LLM providers often train an entire family of models from scratch, each with a different size (number of parameters, e.g. Llama 3.1 8B, 70B, 405B); this is done to aid users targeting different deployment scales, sizes and compute budgets. However, training multiple multi-billion parameter models from scratch is extremely time-, data- and resource-intensive.

Recent work [1] has demonstrated the effectiveness of combining weight pruning with knowledge distillation to significantly reduce the cost of training LLM model families. Here, only the biggest model in the family is trained from scratch; other models are obtained by successively pruning the bigger model(s) and then performing knowledge distillation to recover the accuracy of pruned models.

In this report, we successfully apply the Minitron compression strategy [1] to two state-of-the-art models: Llama 3.1 8B [3] and Mistral NeMo 12B [4], compressing them down to 4B and 8B parameters, respectively. Figure 1 provides a high-level overview of our approach.

While following the original paper [1], we make a key modification: due to lack of access to the original training data, we fine-tune the teacher model on our own dataset before pruning and distillation. We refer to this step as *teacher correction*. Figure 4 shows that omitting teacher correction causes a data distribution mismatch, negatively impacting distillation.

Table 1 provides a summary of our results: our compression strategy yields a state-of-the-art 8B model

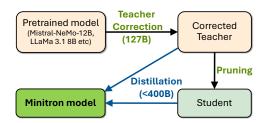


Figure 1 | High-level overview of our proposed pruning and distillation approach. The total number of tokens used for each step is indicated in parentheses.

(MN-Minitron-8B) which outperforms all similarlysized models across the board on common language modeling benchmarks. Our Llama-3.1-Minitron-4B models (both depth and width-pruned variants) also exhibit strong accuracy compared to the teacher Llama 3.1 8B model and the previous-generation Minitron-4B model [1]; among the two variants, the width-pruned variant outperforms the depth-pruned one. In terms of runtime inference performance measured using TensorRT-LLM, the MN-Minitron-8B model provides an average speedup of $1.2\times$ over the teacher Mistral NeMo 12B model. Similarly, the Llama-3.1-Minitron-4B models provide an average speedup of $2.7\times$ and $1.8\times$ for the depth and width pruned variants, respectively, compared to the teacher Llama 3.1 8B model.

Methodology

A high-level overview of our approach is illustrated in Figure 1. Here, the teacher model is first lightly

^{*} Equal contribution.

Benchmarks(shots)	Gemma2	Minitron	Llama-3.1-Minitron		Gemma	Mistral	Llama 3.1	MN-Minitron	Mistral NeMo	
	2B*	4B	4B-Depth	4B-Width	7B	7B	8B	8B	12B-Base	12B-FT
Total Params	2.6B	4.2B	4.5B	4.5B	8.5B	7.3B	8B	8.4B	12.2B	12.2B
Non-Emb. Params	2B	2.6B	3.7B	3.7B	7.7B	7B	7B	7.3B	10.9B	10.9B
Training Tokens	2T	94B	94B	94B	6T	8T	15T	380B	-	+0.1T
Winogrande(5)	70.9	74.0	72.1	73.5	78	78.5	77.3	80.4	82.2	82.7
$Arc_challenge(25)$	55.4	50.9	52.6	55.6	61	60.3	57.9	64.4	65.1	62.3
MMLU(5)	51.3	58.6	58.7	60.5	64	64.1	65.3	69.5	69.0	70.1
Hellaswag(10)	73.0	75.0	73.2	76.1	82	83.2	81.8	83.0	85.2	85.3
GSM8k(5)	23.9	24.1	16.8	41.2	50	37.0	48.6	58.5	56.4	55.7
Truthfulqa(0)	-	42.9	38.2	42.9	45	42.6	45.0	47.6	49.8	48.3
XLSum $en(20\%)$ (3)	-	29.5	27.2	28.7	17	4.8	30.0	32.0	33.4	31.9
MBPP(0)	29.0	28.2	30.7	32.4	39	38.8	42.3	43.8	42.6	47.9
HumanEval(n=20)(0)	20.1	23.3	-	-	32.0	28.7	24.8	36.2	23.8	23.8

Table 1 | Accuracy numbers for our MN-Minitron-8B and Llama-3.1-Minitron-4B models. We compare our models to similarly-sized SoTA open models on a variety of common language modeling benchmarks. All evaluations are conducted by us, except entries marked with * (taken from corresponding papers).

Benchmarks	Gemma 2B	Phi-2 2.7B	Gemma2 2B	Qwen2 1.5B	Minitron 4B	Llama-3.1 4B-Depth	-Minitron 4B-Width
Total Params	2.5B	2.7B	2.6B	1.5B	4.2B	4.5B	4.5B
Non-Emb. Params	2B	2.5B	$_{2\mathrm{B}}$	1.3B	2.6B	3.5B	3.7B
Tokens	3T	1.4T	2T	7T	94B	94B	94B
IFEval	40.5	44.0	64.5	39.8	44.8	42.6	52.4
MT-Bench	5.2	4.3	7.7	5.2	5.6	5.6	6.3
ChatRAG*	33.3	37.6	37.5	32.8	41.1	40.1	44.0
BFCL	47.0	23.1	35.6	32.8	64.2	66.8	64.9

Table 2 | Accuracy numbers for the aligned Llama-3.1-Minitron models. We compare our models to similarly-sized SoTA open aligned models on a variety of benchmarks. All evaluations are conducted by us. * Denotes results obtained on a representative subset of the benchmark. Best in **bold**, second <u>underlined</u>. The alignment of MN-Minitron-8B is underway and will be posted once ready.

finetuned on the target dataset to be used for distillation - we refer to this step as teacher correction. Next, pruning is applied to compress the model, following which distillation is used to recover any lost model accuracy. We refer the reader to the Minitron paper [1] for the full description of the pruning and distillation method.

Pruning

Weight pruning is a powerful and well-known technique for reducing model size. In this report, we focus on structured pruning, where blocks (or channels) of nonzero elements are removed at once from model weights; examples of structured pruning techniques include neuron, attention head, convolutional filter, and depth pruning [1]. In case of LLMs, as shown in Figure 2, we start the pruning process by first computing the importance of each layer, neuron, head, and embedding dimension. We then sort these importance scores to compute a corresponding importance ranking.

Importance Estimation: We use a purely activation-based importance estimation strategy that simultaneously computes sensitivity information for

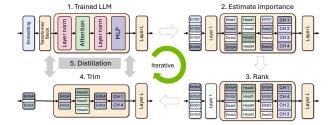


Figure 2 | Pruning and distillation process outlined in the original paper [1]. We follow the same approach in this work.

all the axes we consider (depth, neuron, head, and embedding channel) using a small calibration dataset and only forward propagation passes. We consider depth pruning as a special case and do not combine it with compressing other dimensions.

We compute the importance of each head, neuron and embedding channel by examining the activations produced by the multi-head attention (MHA), multi-layer perceptron (MLP) and LayerNorm layers, respectively. We use a small calibration dataset (1024 samples) for this purpose.

For depth pruning, we consider three distinct met-

rics for evaluating layer importance: (1) LM validation loss, (2) Block Importance (BI) [5] and (3) accuracy on the downstream task. For loss-based ranking, we simply remove a single or a block of contiguous layers and compute its effect on LM loss; this serves as the "importance" or sensitivity of the layer. BI uses the cosine distance between the input and output of a layer or a block of layers. We notice that BI and LM loss metrics are highly correlated but do not produce the most accurate pruned model on downstream tasks as shown in Figures 8 and 9. We thus evaluate layer importance using the Winogrande benchmark [6].

Model Trimming: As shown in Figure 2, for a given architecture configuration, we first rank the elements of each axis according to the computed importance and perform trimming (reshaping) of the corresponding weight matrices directly. For neuron and head pruning, we trim MLP and MHA layer weights, respectively. In the case of embedding channels, we trim the embedding dimension of the weight matrices in MLP, MHA, and LayerNorm layers. The original approach ([1]) uses Neural Architecture Search (NAS) to find the best architecture; in this work, we skip this step and instead utilize the network architecture-related learnings from the original paper.

Retraining with Distillation

We use the term retraining to refer to the accuracy recovery process following pruning. In this work, we explore two retraining strategies: (1) conventional training, leveraging ground truth labels, and (2) knowledge distillation using supervision from the unpruned model (teacher). Knowledge Distillation (KD) involves transfer of knowledge from a larger or more complex model called the teacher to a smaller/simpler model called the student. The knowledge transfer is achieved by having the student model mimic the output and/or the intermediate states of the teacher model. In our case, the uncompressed and pruned models correspond to the teacher and student, respectively. For distillation, we follow best practices from our previous work [1] and use forward KL Divergence loss [7] on the teacher and student logits only. This is illustrated in Figure 3.

Training Details

Pre-training

Llama 3.1 8B [3] and Mistral NeMo [4] 12B are pretrained on different proprietary datasets, which we do not have access to. According to the Llama 3.1 tech report [3], the 8B model is pretrained on 15T

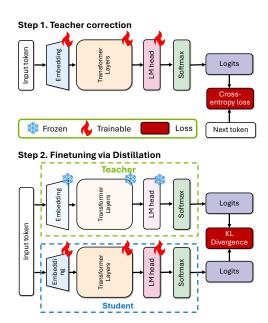


Figure 3 | Overview of Distillation: If the original training data is unavailable, a slight fine-tuning of the teacher model is recommended. Distillation is then performed by minimizing KL divergence on the logits, with the original model as the teacher and the pruned model as the student.

tokens. We start with the corresponding Base models that are openly available online on Hugging Face.

Dataset: We use the Nemotron-4 curated continued training dataset(CT) [8] [9] for all our experiments.

Pruning

Our simplified pruning recipe is based on the best practices outlined in the Minitron paper [1] and is described in the Methodology section. Specifically, for width pruning, we (1) use 12-norm and mean as the aggregation functions across the batch and sequence dimensions, respectively, and (2) perform single-shot pruning, avoiding iterative approaches. For depth pruning, as described in the Methodology section, we follow the observations from Gromov et al. [10] and drop a continuous subgroup of layers that results in the least accuracy drop on Winogrande [6]. In this work, we skip the lightweight neural architecture search (NAS) phase, and go with a manual architecture configuration for both Llama-3.1-Minitron-4B and MN-Minitron-8B. The architectures we come up with are inspired by the Minitron-4B and Minitron-8B models, and are detailed in Table 3. We now describe the pruning recipes for each of our target compressed models:

Llama-3.1-Minitron-4B-Width:

Starting model: Llama 3.1 8B
Hidden dimension: 4096 → 3072

• MLP hidden dimension: $14336 \rightarrow 9216$

• Attention heads: unchanged

• Depth: unchanged

Llama-3.1-Minitron-4B-Depth:

Starting model: Llama 3.1 8BHidden dimension: unchanged

• MLP hidden dimension: unchanged

• Attention heads: unchanged

• Depth: $32 \rightarrow 16$

MN-Minitron-8B:

Starting model: Mistral NeMo 12B
 Hidden dimension: 5120 → 4096

• MLP hidden dimension: $14336 \rightarrow 11520$

• Attention heads: unchanged

• Depth: unchanged

Distillation

Teacher Correction: Using the Mistral NeMo 12B model directly as a teacher performs sub-optimally on our dataset. This is due to the change in distribution of sub-word tokens across the original dataset the teacher model was trained on vs. the dataset being distilled on. To account for this, we first fine-tune the teacher on our dataset using $\sim 127B$ tokens. As shown in Figure 4, such a correction is essential if the original dataset is not available during distillation. We thus apply this technique on both the Mistral-NeMo and Llama-3.1 teacher models. The fine-tuning process has a minor effect on the teacher model's accuracy on downstream tasks, with some tasks improving and some degrading as shown in Table 1. We hypothesize

	LLaMa-3 Width	.1-Minitron-4B Depth	MN-Minitron 8B
Total params	4.5B	4.5B	8.4B
Non-Emb params	3.7B	3.5B	7.3B
Hidden size	3072	4096	4096
Vocabulary	128256	128256	131072
MLP hidden dim	9216	14336	11520
Depth	32	16	40
Attention groups	8	8	8
Query heads	32	32	32
Head dimension	128	128	128

Table $3 \mid$ Architecture details of our compressed models.

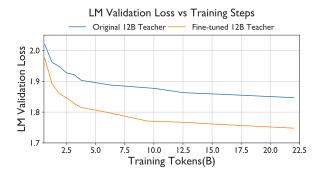


Figure 4 | Training convergence plot for the compressed 8B student model. We compare supervision from the original teacher and the corrected teacher.

this to be an artifact of the dataset used for finetuning.

Retraining: Following the learnings in the Minitron work [1], we opt for logit-only distillation, minimizing the forward KL Divergence [7] loss across the teacher and student probabilities, and ignore the LM cross-entropy loss altogether. Here, the unpruned and pruned models correspond to the teacher and student, respectively. We use the hyperparameters listed in Table 4 during distillation. We use 32 NVIDIA DGX H100 nodes for our training jobs.

	Llama-3.1- Minitron-4B	MN-Minitron 8B
Peak learning rate	1e-4	1e-4
Min learning rate	1e-5	4.5e-7
Warm-up steps	40 steps	60 steps
LR decay schedule	Cosine	Cosine
Global batch size	1152	768
Context length	8192	8192
Total tokens	94B	380B

Table 4 | Hyperparameters used during distillation-based retraining.

Instruction Tuning

To evaluate the instruction-following capabilities of our distilled models, we perform supervised fine-tuning (SFT) on the Llama-3.1-Minitron 4B models using NeMo-Aligner [11] with the instruction tuning dataset used for Nemotron-4 340B [12]. As shown in Table 2, we evaluate the aligned models for instruction- following and roleplay (IFEval [13] and MT-Bench [14]), RAG QA (ChatRAG-Bench [15]), and function-calling capabilities (BFCL [16]).

Analysis

We perform a series of ablation studies to better understand the compression characteristics of these newer models. We report our results in this section.

Width vs Depth Pruning: Figure 5 shows the training curve of Llama-3.1-Minitron-4B pruned for width vs. depth. We notice that width pruning results in smaller initial loss and consistently outperforms the depth-pruned model, despite both variants having the same number of parameters.

Pruning and Distillation: Figure 6 demonstrates orthogonal benefits of our proposed approach with pruning and distillation. We compare (1) random weight initialization and distillation, (2) random pruning and distillation, where components are pruned randomly ignoring the importance scores, (3) our proposed pruning with typical cross entropy based LM loss training and (4) our proposed pruning with distillation-based training. We notice that pruning results in a significantly better starting point compared to random initialization, and also that distillation-based training outperforms conventional training methods while requiring significantly fewer training tokens (up to $50\times$ in our case).

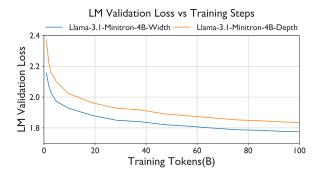


Figure 5 | Convergence of width- and depth-pruned Llama 3.1 8B to 4B models. Width pruning consistently outperforms depth pruning for a given parameter budget.

Teacher Correction: We compare two approaches for teacher correction: (1) pruning and distilling the corrected teacher, and (2) pruning the original teacher and distilling from a continuously corrected teacher. The results in Figure 7 suggest that teacher correction doesn't affect the optimality of pruning, and that distillation from a corrected teacher is crucial. Teacher correction can be performed in parallel with distillation to bridge the gap.



Figure 6 | Training convergence plot for Mistral Nemo 12B compressed model. We compare (a) random initialization with distillation, (b) randomly pruned weights with distillation, (c) pruning with standard LM loss, and (d) our pipeline with pruning and distillation.

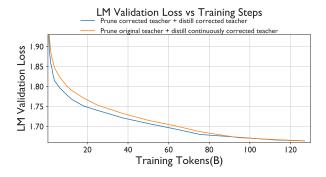


Figure 7 | Training convergence plot for Mistral Nemo 12B compressed model. We compare (1) pruning and distilling the corrected teacher with (2) pruning the original teacher and distilling from a continuously corrected teacher.

Depth Pruning Metrics: when examining how LM validation loss increases as contiguous blocks of layers are removed (Figure 8), we observe that the layers at the beginning and end are the most important. Removing non-contiguous layers can result in even better LM validation loss (the dashed line). However, this observation does not necessarily hold when evaluating downstream task performance. Figure 9 shows that dropping 16 layers selected based on per-layer importance ([5, 17]) yields a random Winogrande accuracy of 0.5, while removing layers 16 to 31 continuously ([10]) results in an accuracy of 0.595. The gap holds during distillation-based retraining and we opt for the latter approach.

Evaluation

Benchmarks following Touvron et al. [18], we evaluate our compressed models on a series of downstream

LM Validation loss for different set of layers dropped

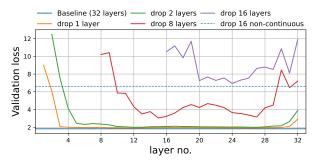


Figure 8 | LM loss value on validation set after removing 1, 2, 8 or 16 contiguous layers with Llama 3.1 8B. For example, the purple line at layer no. 16 indicates the LM loss if we dropped the first 16 layers. Layer no. 17 indicates the LM loss if we leave the first layer intact and drop layers 2 to 17. The dashed line corresponds to LM loss value when removing 16 non-contiguous layers least increasing the loss.

Accuracy for different set of 16 layers dropped

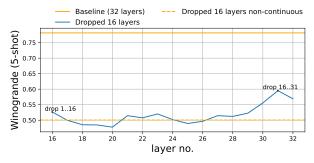


Figure 9 | Accuracy on the Winogrande task when removing 16 contiguous layers with Llama $3.1\,$ 8B. Layer no. 17 indicates the LM loss if we leave the first layer intact and drop layers 2 to 17. The dashed line corresponds to the accuracy when removing 16 non-contiguous layers least increasing the loss.

tasks, including MMLU [19], HumanEval [20] for Python code generation, several question-answering datasets for common-sense reasoning: Arc-C [21], HellaSwag [22], TruthfulQA [23] and WinoGrande [6] and XL-Sum English [24] for summarization. We report the 5-shot performance on MMLU, 5-shot on Winogrande, 25-shot on ARC-Challenge, 10-shot on HellaSwag, 0-shot on 20% of XL-Sum and average pass@1 scores for HumanEval and MBPP. For pass@1 scores we use a temperature of 0.2 and nucleus sampling [25] with top-p = 0.95. For instruction-tuned models, we use MT-Bench [14], Instruction-Following Eval (IFEval) [13], ChatRAG-Bench [15], and Berkeley Function Calling Leaderboard (BFCL) [16].

Base Models

Base model evaluation results are shown in Table 1. Compared to similarly-sized models, MN-Minitron-8B demonstrates superior accuracy across the board, outperforming the recent Llama 3.1 8B model using $40\times$ fewer training tokens (380B vs. 15T). Similarly, the Llama-3.1-Minitron 4B models perform favorably compared to the teacher Llama 3.1 8B model using $150\times$ fewer training tokens (94B vs. 15T); our pruned Llama models also outperform the previous generation Minitron 4B model. We note from Table 1 that the width-pruned variant outperforms the depth-pruned one. These results clearly demonstrate the advantages of our methodology: state-of-the-art accuracy coupled with an order of magnitude improvement in training efficiency.

Instruct Models

The performance of the instruction-tuned Llama-3.1-Minitron 4B variants is shown in Table 2. We compare the Llama-3.1-Minitron 4B variants to other similarly-sized baselines and notice that our models demonstrate strong instruction-following and roleplay capabilities, only lagging behind Gemma2 in IFEval [13] and MT-Bench [14]. On retrieval based question answering (ChatRAG-Bench [15]) and function-calling (BFCL [16]), Minitron models achieve state-of-the-art performance.

Insights

In this Section, we summarize some interesting and surprising observations.

General

- 1. Teacher correction is crucial for distillation to work optimally on a new, unseen dataset. Fine-tuning the teacher with the dataset used for distillation in this manner yields over a 6% reduction in LM validation loss. Teacher correction doesn't affect the optimality of pruning and can even be performed in parallel with distillation.
- 2. In line with the Minitron paper's observations, we require only 380B tokens to achieve state-of-the-art accuracy post pruning with distillation.
- 3. For width pruning, we achieve stronger accuracy by retaining attention heads and pruning the other dimensions (MLP intermediate dimension, embedding channels).

Mistral NeMo 12B to MN-Minitron-8B:

1. Our compressed model outperforms the teacher on two benchmarks, GSM8k and HumanEval after pruning and distillation: GSM8k increases from 55.7% to 58.5% and HumanEval increases from 23.8% to 36.2%. This improvement is likely influenced by the dataset. However, retraining is performed using the distillation loss alone.

Llama 3.1 8B to Llama-3.1-Minitron 4B:

- 1. Width pruning delivers better accuracy with MMLU at 60.5%, while depth pruning yields 58.7%, for Llama-3.1 compression.
- 2. Reasoning ability is impacted further significantly, with GSM8K accuracy at 41.24% for width and 16.8% for depth.
- 3. Depth pruning boosts throughput, achieving \sim 2.7× speedup over Llama-3.1 8B, while width pruning provides $\sim 1.7 \times$ speed up.
- 4. For depth pruning, we observe that dropping contiguous layers from the model is more effective than using non-contiguous, importance-based pruning.

Acknowledgments

This work would not have been possible without contributions from many people at NVIDIA. To mention a few:

Foundational Model: Sharath Turuvekere Sreenivas, Saurav Muralidharan, Raviraj Joshi, Marcin Chochowski, Pavlo Molchanov, Mostofa Patwary, Daniel Korzekwa, Ashwath Aithal, Mohammad Shoeybi, Bryan Catanzaro and Jan Kautz

Alignment: Ameya Sunil Mahabaleshwarkar, Hayley Ross, Brandon Rowlett, Oluwatobi Olabiyi, Shizhe Diao and Yoshi Suhara

Datasets: Sanjeev Satheesh, Jupinder Parmar, Shengyang Sun, Jiaqi Zeng, Zhilin Wang, Yi Dong, Zihan Liu, Rajarshi Roy, Wei Ping, Makesh Narsimhan Sreedhar and Oleksii Kuchaiev

TensorRT-LLM: Bobby Chen, James Shen and Chenhan Yu

Hugging Face Support: Ao Tang, Yoshi Suhara and Greg Heinrich

References

[1] Saurav Muralidharan, Sharath Turuvekere Sreenivas, Raviraj Joshi, Marcin Chochowski, Mostofa Patwary, Mohammad Shoeybi, Bryan Catanzaro, Jan Kautz, and Pavlo Molchanov. Compact language models via pruning and knowledge distillation. arXiv preprint arXiv:2407.14679, 2024.

- [2] Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, 12 2023.
- [3] Abhimanyu Dubey and Abhinav Jauhri et al. The llama 3 herd of models, 2024.
- [4] Mistral AI team. Mistral nemo. https://mistral.ai/news/mistral-nemo, 2024. Accessed: 2024.
- [5] Xin Men, Mingyu Xu, Qingyu Zhang, Bingning Wang, Hongyu Lin, Yaojie Lu, Xianpei Han, and Weipeng Chen. ShortGPT: Layers in Large Language Models are More Redundant Than You Expect, 2024.
- [6] Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. WinoGrande: An adversarial winograd schema challenge at scale. *Commun. ACM*, 64(9), 2021.
- [7] Solomon Kullback and Richard A. Leibler. On information and sufficiency. Annals of Mathematical Statistics, 22(1):79–86, 1951.
- [8] Jupinder Parmar, Shrimai Prabhumoye, Joseph Jennings, Mostofa Patwary, Sandeep Subramanian, Dan Su, Chen Zhu, Deepak Narayanan, Aastha Jhunjhunwala, Ayush Dattagupta, Vibhu Jawa, Jiwei Liu, Ameya Mahabaleshwarkar, Osvald Nitski, Annika Brundyn, James Maki, Miguel Martinez, Jiaxuan You, John Kamalu, Patrick LeGresley, Denys Fridman, Jared Casper, Ashwath Aithal, Oleksii Kuchaiev, Mohammad Shoeybi, Jonathan Cohen, and Bryan Catanzaro. Nemotron-4 15b technical report, 2024.
- [9] Jupinder Parmar, Sanjev Satheesh, Mostofa Patwary, Mohammad Shoeybi, and Bryan Catanzaro. Reuse, don't retrain: A recipe for continued pretraining of language models, 2024.
- [10] Andrey Gromov, Kushal Tirumala, Hassan Shapourian, Paolo Glorioso, and Daniel A. Roberts. The unreasonable ineffectiveness of the deeper layers. 2024.
- [11] Gerald Shen, Zhilin Wang, Olivier Delalleau, Jiaqi Zeng, Yi Dong, Daniel Egert, Shengyang Sun, Jimmy Zhang, Sahil Jain, Ali Taghibakhshi, Markel Sanz Ausin, Ashwath Aithal, and Oleksii Kuchaiev. Nemoaligner: Scalable toolkit for efficient model alignment, 2024.
- [12] Nvidia, :, Bo Adler, Niket Agarwal, Ashwath Aithal, Dong H. Anh, Pallab Bhattacharya, Annika Brundyn, Jared Casper, Bryan Catanzaro, Sharon Clay, Jonathan Cohen, Sirshak Das, Ayush Dattagupta,

Olivier Delalleau, Leon Derczynski, Yi Dong, Daniel Egert, Ellie Evans, Aleksander Ficek, Denys Fridman, Shaona Ghosh, Boris Ginsburg, Igor Gitman, Tomasz Grzegorzek, Robert Hero, Jining Huang, Vibhu Jawa, Joseph Jennings, Aastha Jhunjhunwala, John Kamalu, Sadaf Khan, Oleksii Kuchaiev, Patrick LeGresley, Hui Li, Jiwei Liu, Zihan Liu, Eileen Long, Ameya Sunil Mahabaleshwarkar, Somshubra Majumdar, James Maki, Miguel Martinez, Maer Rodrigues de Melo, Ivan Moshkov, Deepak Narayanan, Sean Narenthiran, Jesus Navarro, Phong Nguyen, Osvald Nitski, Vahid Noroozi, Guruprasad Nutheti, Christopher Parisien, Jupinder Parmar, Mostofa Patwary, Krzysztof Pawelec, Wei Ping, Shrimai Prabhumoye, Rajarshi Roy, Trisha Saar, Vasanth Rao Naik Sabavat, Sanjeev Satheesh, Jane Polak Scowcroft, Jason Sewall, Pavel Shamis, Gerald Shen, Mohammad Shoeybi, Dave Sizer, Misha Smelyanskiy, Felipe Soares, Makesh Narsimhan Sreedhar, Dan Su, Sandeep Subramanian, Shengyang Sun, Shubham Toshniwal, Hao Wang, Zhilin Wang, Jiaxuan You, Jiaqi Zeng, Jimmy Zhang, Jing Zhang, Vivienne Zhang, Yian Zhang, and Chen Zhu. Nemotron-4 340b technical report, 2024.

- [13] Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. Instruction-following evaluation for large language models. arXiv preprint arXiv:2311.07911, 2023.
- [14] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, Hao Zhang, Joseph E Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine, editors, Advances in Neural Information Processing Systems, volume 36, pages 46595–46623. Curran Associates, Inc., 2023.
- [15] Zihan Liu, Wei Ping, Rajarshi Roy, Peng Xu, Chankyu Lee, Mohammad Shoeybi, and Bryan Catanzaro. Chatqa: Surpassing gpt-4 on conversational qa and rag. arXiv preprint arXiv:2401.10225, 2024.
- [16] Fanjia Yan, Huanzhi Mao, Charlie Cheng-Jie Ji, Tianjun Zhang, Shishir G. Patil, Ion Stoica, and Joseph E. Gonzalez. Berkeley function calling leaderboard. https://gorilla.cs.berkeley.edu/blogs/ 8_berkeley_function_calling_leaderboard.html, 2024.
- [17] Shoaib Ahmed Siddiqui, Xin Dong, Greg Heinrich, Thomas Breuel, Jan Kautz, David Krueger, and Pavlo Molchanov. A deeper look at depth pruning of llms. arXiv preprint arXiv:2407.16286, 2024.
- [18] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti

Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models. ArXiv, abs/2307.09288, 2023.

- [19] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. In *International Conference on Learning Representations*, 2021.
- [20] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde, Jared Kaplan, Harrison Edwards, Yura Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, David W. Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William H. Guss, Alex Nichol, Igor Babuschkin, Suchir Balaji, Shantanu Jain, Andrew Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew M. Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code. ArXiv, abs/2107.03374, 2021.
- [21] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try ARC, the AI2 reasoning challenge. ArXiv, abs/1803.05457, 2018.
- [22] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. HellaSwag: Can a machine really finish your sentence? In Anna Korhonen, David Traum, and Lluís Màrquez, editors, Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Florence, Italy, July 2019. Association for Computational Linguistics.

- [23] Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods, 2022.
- [24] Tahmid Hasan, Abhik Bhattacharjee, Md Saiful Islam, Kazi Samin, Yuan-Fang Li, Yong-Bin Kang, M. Sohel Rahman, and Rifat Shahriyar. Xl-sum: Large-scale multilingual abstractive summarization for 44 languages, 2021.
- [25] Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. ArXiv, abs/1904.09751, 2019.