StableLM-3B-4E1T Technical Report

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Abstract

We introduce StableLM-3B-4E1T, a 3 billion parameter language model pre-trained under the multi-epoch regime. We explore the impact of repeated tokens on downstream performance, training on 1 trillion tokens for 4 epochs. Our findings contribute to the ongoing research in scaling data-constrained language models.

1 Introduction

StableLM-3B-4E1T [1] is a 3 billion (3B) parameter language model pre-trained under the multi-epoch regime to study the impact of repeated tokens on downstream performance. Given the prior success in this area (Taylor et al., 2022 and Yi Tay* and Metzler, 2022), we ***train on 1 trillion (1T) tokens for 4 epochs (4E)*** following the observations of Muennighoff et al. (2023) in which they find "training with up to 4 epochs of repeated data yields negligible changes to loss compared to having unique data." Further inspiration for the token count is taken from (De Vries, 2023), which suggests a 2.96B model trained for 2.85 trillion tokens achieves a similar loss to a Chinchilla compute-optimal 9.87B language model ($k_n = 0.3$).

2 Model Architecture

The model is a decoder-only transformer similar to the LLaMA (Touvron et al., 2023) architecture with the following modifications:

- **Position Embeddings:** Rotary Position Embeddings (Su et al., 2023) applied to the first 25% of head embedding dimensions for improved throughput following Black et al. (2022).
- **Normalization:** LayerNorm (Ba et al., 2016) with learned bias terms as opposed to RMSNorm (Zhang and Sennrich, 2019).
- **Tokenizer:** GPT-NeoX (Black et al., 2022).

Parameter	Value
Parameters	2,795,443,200
Hidden Size	2560
Layers	32
Heads	32
Sequence Length	4096

Table 1: Model Architecture Details

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[1] https://huggingface.co/stabilityai/stablelm-3b-4e1t

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3 Training Data

The dataset is comprised of a filtered mixture of open-source large-scale datasets available on the HuggingFace Hub: Falcon RefinedWeb extract (Penedo et al., 2023), RedPajama-Data (Computer, 2023), and The Pile (Gao et al., 2020), both without the *Books3* subset, and StarCoder (Li et al., 2023). The complete list is provided in Table 1.

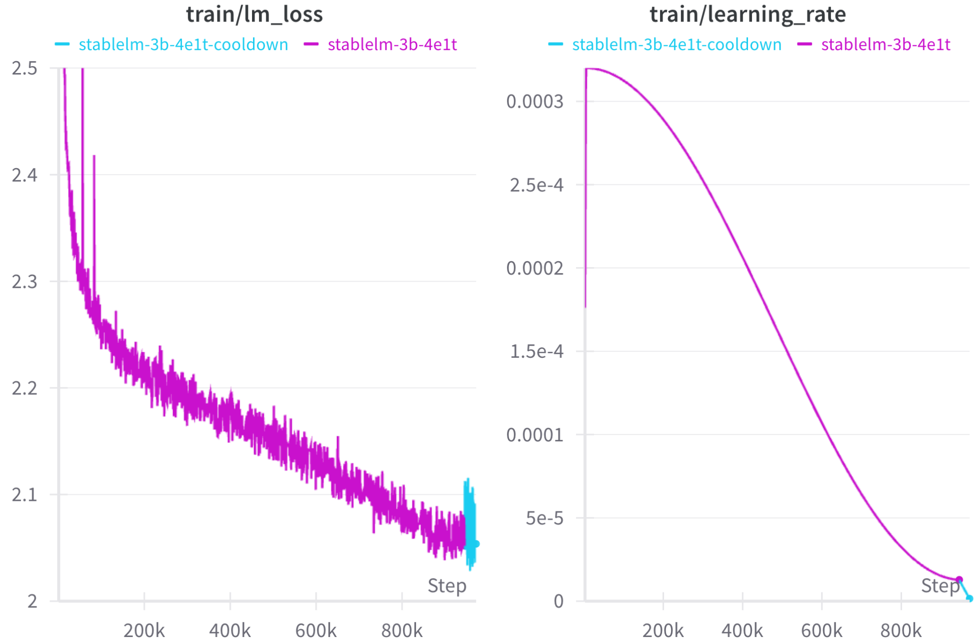
Dataset	Subset	Num Tokens (NeoX)	Num Docs	Category
The Pile	ArXiv	19,769,458,882	1,441,920	Academic
The Pile	PubMed	22,378,915,742	2,964,625	Academic
S2ORC		60,552,319,208	11,592,936	Academic
The Pile	PhilPapers	644,077,299	33,881	Academic
S2ORC	peS2o	57,200,107,871	38,811,179	Academic
The Pile	PG-19	4,719,327,141	50,579	Books
RefinedWeb		580,957,303,522	967,989,228	Web
RedPajama	Common Crawl (2023)	188,371,605,706	111,402,716	Web
RedPajama	C4	174,769,707,653	364,868,892	Web
The Pile	OpenWebText2	8,947,174,650	8,012,025	Web
RedPajama	StackExchange	20,544,276,837	29,825,086	Social
The Pile	UbuntuIRC	1,871,044,039	2,807	Social
The Pile	HackerNews(2006-2020)	2,031,470,476	1,571,968	Social
The Pile	EuroParl	1,562,068,114	69,814	Law
The Pile	FreeLaw	13,805,827,414	4,542,840	Law
Pile Of Law		16,377,540,899	3,096,719	Law
DM Math		3,728,203,638	972,502	Math
AMPS		324,711,403	2,635,350	Math
RedPajama	GitHub	58,930,922,707	28,793,312	Code
StarCoder	C	7,197,443,940	204,250	Code
StarCoder	CPP	8,944,383,599	221,536	Code
StarCoder	Java	11,801,463,022	388,908	Code
StarCoder	JavaScript	8,451,649,925	354,224	Code
StarCoder	Python	12,073,208,678	475,750	Code
RedPajama	Wiki	24,839,086,595	29,834,171	Wiki
	Total	1,310,793,298,960		

Figure 1: Open-source datasets used for multi-epoch training. Note that the total token count does not account for the reduced size after downsampling C4, Common Crawl (2023), and GitHub to obtain 1T tokens.

The data mixture is primarily based on the reported DoReMi (Xie et al., 2023) optimal mixture for The Pile domains. Given the extensive web data, we recommend fine-tuning base StableLM-3B-4E1T for your downstream tasks.

4 Training Procedure

The model is trained for 972k steps in bfloat16 precision with a global context length of 4096 instead of the multi-stage ramp-up from 2048-to-4096 as done for StableLM-Alpha v2. The batch size is set to 1024 (4,194,304 tokens). We optimize with AdamW (Loshchilov and Hutter, 2017) and use linear warmup for the first 4.8k steps, followed by a cosine decay schedule to 4% of the peak learning rate. Early instabilities are attributed to extended periods in high learning rate regions. We do not incorporate dropout (Srivastava et al., 2014) due to the model's relatively small size. Detailed hyperparameters are provided in the model configuration in the `StableLM` repository.



(a) Training Loss (b) Learning Rate Schedule

Figure 2: Training Dynamics

During training, we evaluate natural language benchmarks and observe steady improvements throughout training until the tail end of the learning rate decay schedule. For this reason, we decided to linearly **cool down** the learning rate towards 0, similar to Zhai et al. (2022), in hopes of squeezing out performance. We plan to explore alternative schedules in future work.

Furthermore, our initial pre-training stage relies on the flash-attention API (Dao, 2023) with its out-of-the-box triangular causal masking support. This forces the model to attend similarly to different documents in a packed sequence. In the cool-down stage, we instead reset position IDs and attention masks at EOD tokens for all packed sequences after empirically observing improved sample quality (read: less repetition) in a concurrent experiment. We hypothesize that this late adjustment leads to the notable degradation in byte-length normalized accuracies of ARC-Easy (Clark et al., 2018) and SciQ (Johannes Welbl, 2017).

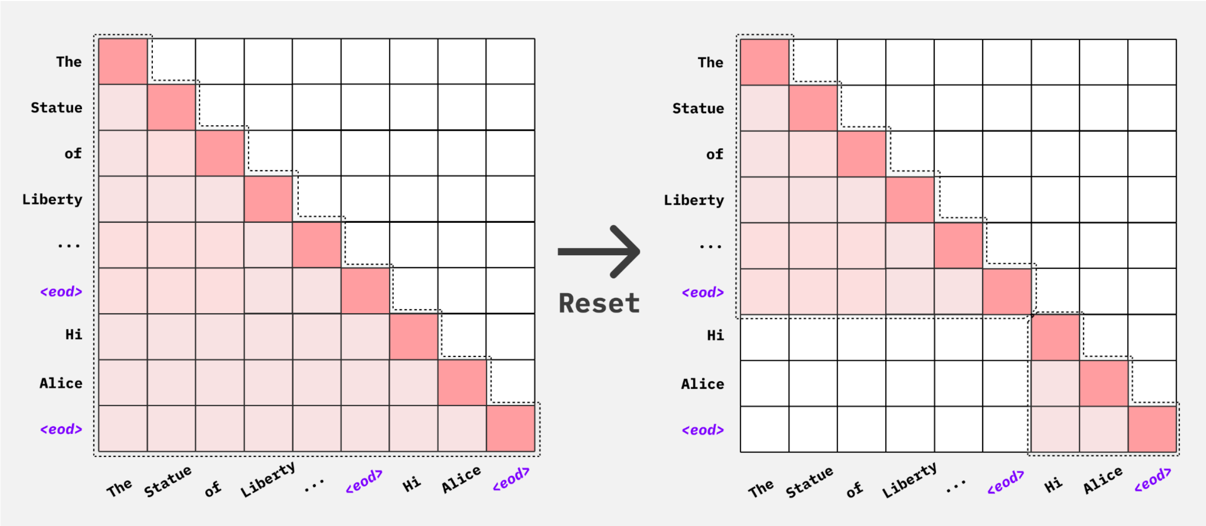
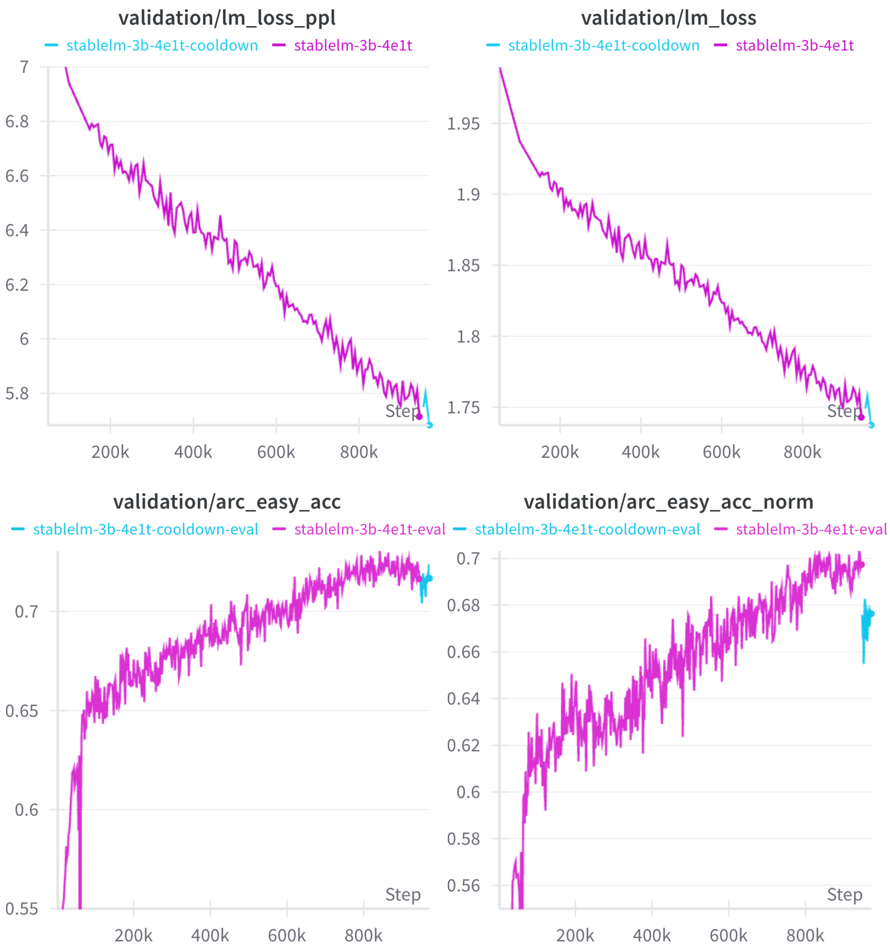


Figure 3: Toy demonstration of attention mask resetting.

Data composition was modified during the cool-down. Specifically, we remove Ubuntu IRC, OpenWebText, HackerNews, and FreeLaw for quality control and further NSFW filtering while upsampling C4. The distribution shift is likely responsible for the increased loss (+0.02 nats) from the initial stage.

See the plots below for validation dynamics across our hold-out set and common NLP benchmarks.



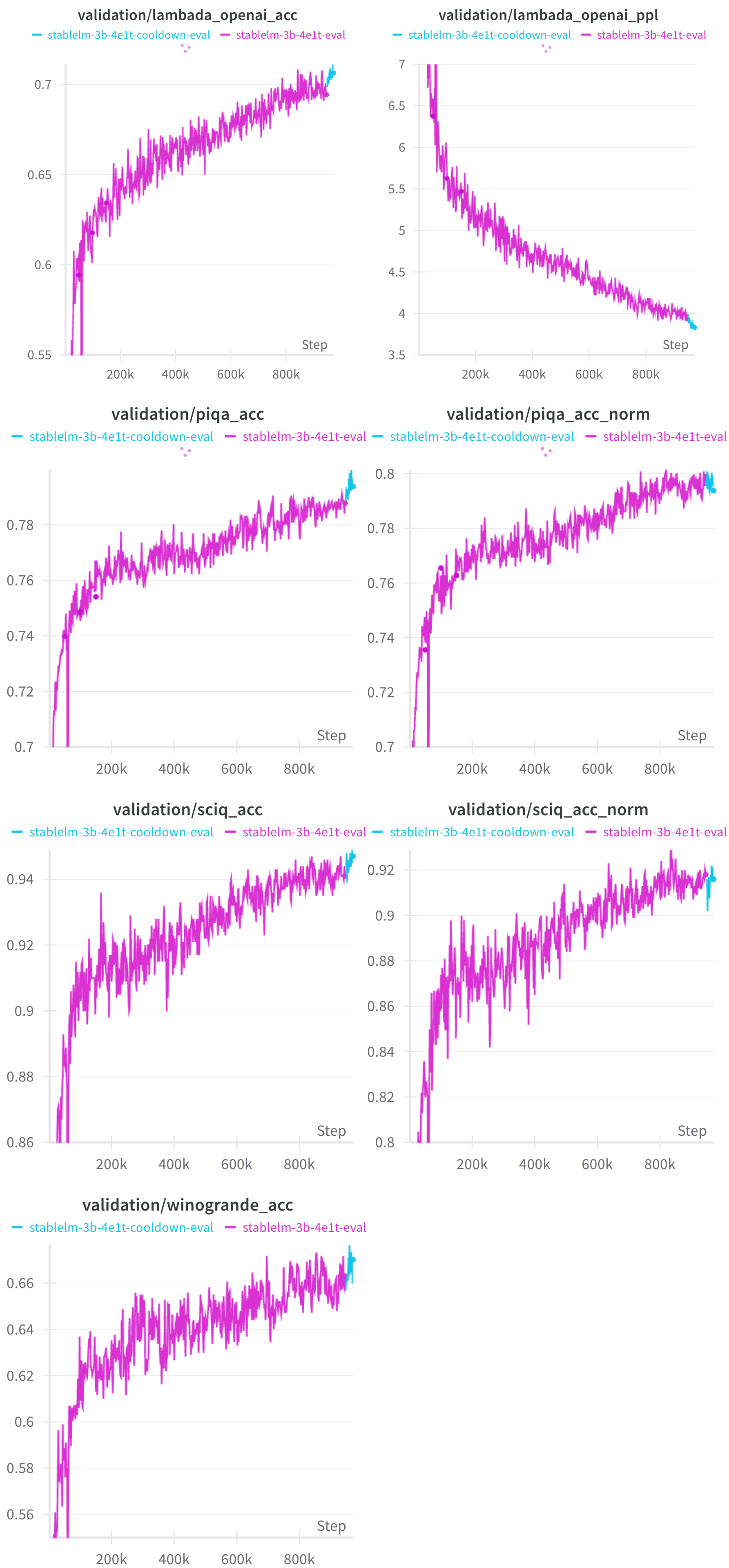


Figure 4: Validation Dynamics

Note: The released checkpoint is taken from step 970k according to validation loss and average downstream performance.

5 Downstream Results

The following zero-shot evaluations are performed with EleutherAI's `lm-evaluation-harness` (Gao et al., 2021) using the `lm-bench` branch of Stability AI's fork.

Model	Avg	ARC-C	ARC-E	BoolQ	HSwag	LAMB	OBQA	PIQA	SciQ	Wino
LLaMA 2 7B	68.75	43.00	76.26	77.74	75.94	73.47	31.40	77.75	93.60	69.61
Qwen-7B	67.91	45.39	67.38	74.56	88.85[a]	69.67	32.20	73.99	93.20	65.98
Falcon-7B	67.83	40.27	74.41	73.55	76.35	74.56	30.60	79.49	94.00	67.25
MPT-7B	67.36	40.53	74.92	73.94	76.17	68.64	31.40	78.89	93.70	68.03
StableLM 3B 4E1T	66.93	37.80	72.47	75.63	73.90	70.64	31.40	79.22	94.80	66.54
Baichuan2-7B Base	66.93	42.24	75.00	73.09	72.29	70.99	30.40	76.17	94.60	67.56
StableLM-Base-Alpha-7B v2	66.89	38.48	73.19	70.31	74.27	74.19	30.40	78.45	93.90	68.82
Open LLaMA 7B v2	66.32	38.82	71.93	71.41	74.65	71.05	30.20	79.16	93.80	65.82
Phi-1.5	65.57	44.45	76.14	74.53	62.62	52.75	37.60	76.33	93.20	72.53
GPT-NeoX-20B	65.57	37.88	72.90	69.48	71.43	71.98	29.80	77.42	93.10	66.14
BTLM-3B-8K-Base[b]	63.59	34.90	70.45	69.63	69.78	66.23	27.60	75.84	92.90	64.96
Pythia 12B	62.69	31.83	70.20	67.31	67.38	70.64	26.40	76.28	90.20	64.01
Open LLaMA 3B v2	62.43	33.87	67.59	65.69	69.99	66.74	26.00	76.66	92.40	62.90
GPT-J 6B	62.34	33.96	66.96	65.44	66.24	68.23	29.00	75.57	91.50	64.17
Pythia-6.9B	60.58	31.83	67.21	64.01	63.88	67.01	25.80	75.08	89.80	60.62
Pythia 2.8B	58.52	30.12	63.47	64.13	59.44	65.15	23.80	74.10	88.20	58.25

[a] Outlier results
[b] Previous 3B Pre-Trained SOTA

Table 2: Zero-shot performance across popular language modeling and common sense reasoning benchmarks. `lm-eval` results JSONs can be found in the `evals` directory of the `StableLM` repository.

StableLM-3B-4E1T achieves state-of-the-art performance (September 2023) at the 3B parameter scale for open-source models and is competitive with many of the popular contemporary 7B models, even outperforming our most recent 7B StableLM-Base-Alpha-v2.

6 System Details

Hardware: StableLM-3B-4E1T was trained on the Stability AI cluster across 256 NVIDIA A100 40GB GPUs (AWS P4d instances). Training began on August 23, 2023, and took approximately 30 days to complete.

Software: We use an internal fork of GPT-NeoX (Andonian et al., 2023), train under 2D parallelism (Data and Tensor Parallel) with ZeRO-1 (Rajbhandari et al., 2020), and rely on flash-attention as well as SwiGLU and Rotary Embedding kernels from FlashAttention-2 (Dao, 2023).

Figure 5: Throughput Logging. TFLOPS are estimated using GPT-NeoX's get_flops function.

7 Conclusion

In this technical report, we present StableLM-3B-4E1T, a 3 billion parameter language model trained on 1 trillion tokens for 4 epochs. Our results provide further evidence for the claims in Muennighoff et al. (2023) at the trillion token scale, suggesting multi-epoch training as a valid approach to improving downstream performance when working under data constraints.

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