The Stability-Efficiency Dilemma: Investigating Sequence Length Warmup for Training GPT Models

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Abstract

Recent works have demonstrated great success in pre-training large-scale autoregressive language models (e.g., GPT-3) on massive GPUs. To reduce the wall-clock training time, a common practice is to increase the batch size and learning rate. However, such practice is often brittle and leads to a so-called stability-efficiency dilemma: increasing the batch sizes and learning rates leads to better training efficiency but can also result in training instability, leading to poor generalization accuracy or failed runs. To better understand this phenomenon, we conduct an in-depth analysis on large-scale pre-training experiments replicating the GPT-2 model with public dataset. We find that there is a strong correlation between training instability and extreme values of gradient variance. We further identify that samples with long sequence lengths contribute to these extreme gradient variance values, especially at the beginning of the training, indicating that long sequence length can be a main source of training instability.

Based on the analysis, we present a simple yet effective Sequence Length Warmup method that aims to solve the training stability-efficiency dilemma by avoiding extreme gradient variance values. Moreover, we present a lightweight tuning strategy that allows us to tune our method with just a small portion of the expensive full training. Experiments replicating GPT-2 models (117M and 1.5B) show that our approach enables stable training with 8x larger batch size and 4x larger learning rate, whereas the baseline approach struggles with training instability. To achieve the same or better zero-shot evaluation results, our method reduces the required number of training tokens and wall clock time by up to 2.2x and 3.7x, respectively. Experiments replicating GPT-3 model (125M) show that our approach enables stable training with 8x larger batch size and 40x larger learning rate, and retains 99% of the zero-shot accuracy on 11 tasks using 10x less data and 12x less time compared to the original GPT-3 training recipe, while the baseline diverges under the same settings and only retain 95% of accuracy under lower learning rate.

1 Introduction

Large-scale Transformer-based language models have achieved great success in many natural language processing tasks [44, 11]. Among them, large-scale autoregressive models, such as GPT-3 [6], have attracted lots of attention due to their superior performance on zero-shot generalization, i.e., they can perform a wide range of tasks despite that they are not explicitly trained on. However, pre-training GPT models raises huge challenges on training efficiency and less-discussed training instability issues. On the efficiency side, as the model size continues to grow from a few hundreds of millions (e.g., GPT [29]), to billion-scale parameters (1.5B GPT-2 [31]), and to more recent hundreds of billions of parameters (175B GPT-3 [6]), the training cost also increases exponentially: it requires 9.2 days on 512 V100 GPUs to train a 8.3B GPT-2 [38], and 47.8 days on 2240 A100 GPUs to train a

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

530B GPT-3-style model [24]. Such a long training time makes it almost infeasible for most research labs and practitioners to reproduce these models. Various solutions have been proposed to reduce the training wall clock time of these large models [38, 23, 33]. However, many solutions require using more GPUs or sophisticated system techniques.

In this work, we investigate speeding up the pre-training of GPT-style models via exploiting data efficiency, not at the cost of excessive hardware resources. In particular, in a distributed training environment, increasing the batch sizes and/or using more aggressive learning rates can make the model converge faster [39]. However, it has been observed that larger batch sizes and learning rates can make large-scale GPT model training more difficult, e.g., causing training instability that leads to divergence or slow convergence [47, 9]. To investigate this training instability issue, we conduct a thorough study of the GPT-2 pre-training task [31, 38] with different models sizes under various batch sizes, learning rates, and sequence lengths. We find an **stability-efficiency dilemma**:

- A larger batch size (and larger learning rate) increases the per-iteration computational efficiency but with increasing likelihood of training instability and even divergence.
- A smaller batch size makes the training more stable but decreases the per-step computation efficiency significantly.

We find it difficult to overcome this dilemma by existing techniques such as extra gradient clipping. More recent proposed techniques such as batch size warmup proposed in [6] does not provide stability benefit in our evaluations. Recently, Shortformer[28] shows that by adding an additional first training stage with a shorter sequence length, language models can achieve the same dev. set perplexity with shorter total training time. However, (1) its main focus is to purely improve training efficiency instead of solving the efficiency-stability dilemma, and our evaluations show that Shortformer's 2-stage approach is insufficient for overcoming the training instability issue for large models (Section 5.1), (2) it is primarily evaluated on small scale transformer models (247M) on WikiText datasets (103M tokens) without considering large-scale generative models like GPT with hundreds or even billions of parameters, and (3) it does not discuss how to choose some of the important hyperparameters, which are very expensive to figure out for large-scale model training.

Inspired by Shortformer, we investigate the importance of sequence length in training GPT models and find that it plays an important role in both training stability and efficiency. Based on our investigation, we propose a simple yet effective method called **Sequence Length Warmup (SLW)**, which starts training with short sequences and gradually increases the length. We observe that our approach enables stable and efficient training with much larger batch sizes and learning rates than baseline approaches. Specifically, we make the following contributions: (1) We conduct an extensive study of the GPT-2 pre-training task, which provides detailed insights about the training stability-efficiency dilemma, the correlation between instability and gradient variance outliers, and how sequence length plays a critical role (Section 3). (2) Based on the study, we present a simple yet effective sequence length warmup method for GPT-style model (and autoregressive model in general) that enables stable training with improved training efficiency. We also identify a lightweight hyperparameter tuning strategy for the approach, which identifies promising hyperparameters by only incurring a small fraction of the expensive total pre-training cost (Section 4). The implementation of our approach as well as the necessary changes to the GPT-2/3 pre-training framework has been open sourced in a deep learning optimization library (name hidden to maintain anonymity). (3) We conduct large-scale experiments to demonstrate the proposed work's ability to provide superior training stability and efficiency at the same time (Section 5). Our empirical results show that:

- SLW enables stable and efficient training with 8x larger batch size and 4x larger learning rate on GPT-2 (117M and 1.5B) and GPT-3 (125M) models with public datasets, while the baseline and relate works struggle with instability under the same settings. To achieve the same or better zero-shot WikiText-103/LAMBADA evaluation results at the end of training, SLW reduces the required number of training tokens and wall clock time by up to 2.2x and 3.7x, respectively.
- For GPT-3 experiments we study an even more aggressive training scenario where only 10% of data can be used. Our method, with 8x larger batch size and 40x larger learning rate than the original GPT-3 training recipe, is able to maintain the training stability, retaining 99% of the zero-shot accuracy on 11 evaluation tasks, and use 10x less data and 12x less time. Without our method, the baseline has unrecoverable divergence under the same settings, and can only retain 95% of the zero-shot accuracy after lowering learning rate to 30x.

2 Background and Related Work

Language Model Pre-training: The accuracy of transformer-based language models grows substantially with its model size [29, 31, 6]. Today, a large language model such as GPT-3 [6] contains up to 175B parameters, and recent studies show that model accuracy can continue to improve with even larger model sizes [16]. However, training these large models often incurs excessively long training time and training difficulties [6]. Therefore, there are a lot of demands of performing efficient and stable training for large-scale LMs. To have the pre-training finished in a reasonable amount of time, the most common way is to leverage data parallelism to train models on multiple GPUs. However, the speedup gains often saturate beyond a few tens of GPUs, because communication becomes the major bottleneck, i.e., the workers will spend more time communicating gradients than computing them, as the number of GPUs increases. To mitigate this bottleneck, recent works such as 1-bit Adam [41] have studied gradient compression and demonstrate their effectiveness against auto-encoding models such as BERT [11]. An alternative approach to alleviate these overheads is to use large batch sizes. For example, LAMB [50] and 1-bit LAMB [20] enable stable and efficient distributed BERT pre-training with batch size up to 64K/32K (for sequence length 128/512, i.e., 8M/16M tokens per batch) while maintaining the sample-wise convergence speed. For encoder-decoder models, T5 [32] uses batch size up to 2K (for sequence length 512, i.e., 1M tokens per batch). For autoregressive models such as the GPT family [29, 31, 6], existing works use batch size up to 1.6K (for sequence length 2K, i.e, 3.2M tokens per batch). Despite the benefit of reduced communication overhead, large-batch training is sensitive to hyperparameters and often leads to issues such as slow convergence, training instabilities, and model divergence. For example, recently a research project shared that they are dealing with challenging training instability issues when pre-training a 104B GPT-style model with batch size 2K [47], and another work on a 540B model with batch size 2K observed spikes in the loss roughly 20 times during training, despite the fact that gradient clipping was enabled [9].

Curriculum Learning: Our method can be viewed as a kind of curriculum learning (CL) [12, 37, 2], which presents easier/simpler examples earlier during training and gradually increases the sample difficulties[1]. Comparing with traditional CL works which focus on solely improving the convergence speed under the same batch size, learning rate and other hyperparameters, our work is motivated by the stability-efficiency dilemma and we aim to achieve both efficient convergence and better stability by enabling stable training with more aggressive hyperparameters. To our knowledge, we are the first to investigate and confirm that certain curriculum learning method can provide a dual stability-efficiency benefit. Moreover, although CL was explored and verified for NLP one-stage and fine-tuning tasks [18, 5, 54, 27, 55, 34, 35, 42, 48], there are only a few works explore curriculum learning for language model pre-training [28, 53, 7].

3 GPT-2 Pre-training Stability-Efficiency Analysis

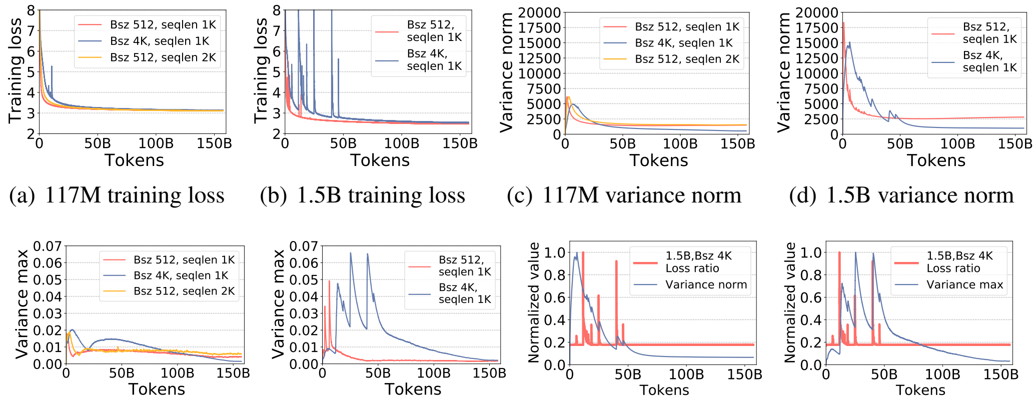
In this section we perform an in-depth analysis of pre-training tasks (without our method) replicating the GPT-2 models with public data. We follow the training pipeline from the NVIDIA Megatron-LM work [38][2]. All of the experiments are performed on 128 NVIDIA V100 GPUs (32GB memory). There are 16 nodes and 8 GPUs per node. GPUs inside the same node are connected by NVLink 2.0, and nodes are connected by a 100 Gigabit InfiniBand EDR inter-node network. We evaluate two GPT-2 model sizes from the original GPT-2 work [31]: 117M parameters (12 layers, 768 hidden size, 12 attention heads) and 1.5B parameters (48 layers, 1600 hidden size, 25 attention heads). For training data, we collect and use the same dataset blend as the Megatron-LM work: Wikipedia [11], CC-Stories [43], RealNews [52], and OpenWebtext [30].

We evaluate two sets of training parameters. The first set follows the Megatron-LM work: batch size 512, 300K total training steps (157B tokens), and learning rate 1.5×10^{-4} with a linear warmup of 3K steps and a single cycle cosine decay over the remaining 297K steps (1×10^{-5} min. learning rate). The second parameter set tests a more aggressive training strategy: batch size 4K ($8\times$ larger), 37.5K total training steps (157B tokens[3]), and learning rate 6×10^{-4} ($4\times$ larger) with a linear warmup of 3K steps and a single cycle cosine decay over the remaining 34.5K steps (same min. learning rate). For sequence length/context size, we mainly use 1K which is the default for GPT-2. But we also test 2K (on the 117M model with batch size 512 and 157B tokens) which is the default for GPT-3.

[1]The shorter sequences are not necessarily easier but can be viewed as simpler examples since there are less context to embed.

[2]https://github.com/NVIDIA/Megatron-LM

[3]For pre-training it is common to keep the number of training tokens the same for fair comparison.



(a) 117M training loss (b) 1.5B training loss (c) 117M variance norm (d) 1.5B variance norm

(e) 117M variance max (f) 1.5B variance max (g) Var norm correlation (h) Var max correlation

Figure 1: Training loss, Adam variance norm/max element, and correlations between loss spikes and variance norm/max during GPT-2 pre-training (without the proposed method) under different model sizes, batch sizes (and LR), and sequence lengths.

All experiments are performed with mixed precision/FP16 training, Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1 \times 10^{-8}$) [17], 0.01 weight decay, same random seed, and gradient clipping at 1.0.

The stability-efficiency dilemma: Figure 1(a) and 1(b) present the training loss curves of 5 baseline cases under different model sizes, batch sizes (and LR), and sequence lengths. At 117M, the baseline has a few training loss spikes at batch size 4K. At 1.5B, the baseline has many loss spikes when training with either batch size 512 or 4K. As an indicative measurement to quantitatively study training instability, we define "loss ratio" which measures the ratio between the current step training loss and the minimum loss among all previous steps. A ratio larger than 1.0 means that current step's loss is larger than the previous minimum loss, thus larger ratio indicates a larger loss spike and training instability. Table 1 summarizes the number of steps with loss ratio larger than 1.2, and the maximum loss ratio during the training. At 117M model size only the baseline with batch size 4K has high loss ratios up to 1.421. At 1.5B model size the baseline with both batch size 512 and 4K has much more steps with large loss ratios, and with the maximum loss ratio as high as 5.65. Baseline with batch size 4K is less stable than baseline with batch size 512, indicating that larger batch sizes could lead to more training instability risks. In Appendix A.2.1 we show that larger learning rates under the same batch size could also increase training instability.

Table 1: Measuring training instability by the ratio between the current step training loss and the minimum loss among all previous steps. Larger ratios (esp. those greatly larger than 1.0) indicate larger training instability/divergence. Proposed work (SLW) and related works (last two rows) are discussed in Section 5.

Case	Pre-training parameters	#steps with loss ratio > 1.2 (% of total steps)	max loss ratio
117M:			
1: Baseline	bsz512-seqlen1K	0 (0.0%)	1.05
2: SLW 60K	bsz512-seqlen1K	0 (0.0%)	1.06
3: Baseline	bsz4K-seqlen1K	22 (0.06%)	1.42
4: SLW 20K	bsz4K-seqlen1K	0 (0.0%)	1.02
5: Baseline	bsz512-seqlen2K	0 (0.0%)	1.04
6: SLW 110K	bsz512-seqlen2K	0 (0.0%)	1.04
1.5B:			
7: Baseline	bsz512-seqlen1K	114 (0.04%)	2.10
8: SLW 270K	bsz512-seqlen1K	0 (0.0%)	1.06
9: Baseline	bsz4K-seqlen1K	1381 (3.68%)	5.65
10: SLW 45K	bsz4K-seqlen1K	0 (0.0%)	1.02
11: Shortformer	bsz4K-seqlen1K	219 (0.4%)	2.86
12: Bsz Warmup	bsz4K-seqlen1K	1179 (2.01%)	4.32

Training instability are undesirable because (1) it could lead to divergence that never recover as in [47] and our GPT-3 experiments (Section 5.2); (2) in our GPT-2 case it leads to worse convergence, validation loss, and zero-shot downstream task accuracy. Table 2 summarizes the zero-shot WikiText-103/LAMBADA evaluation results. For both 117M and 1.5B models, increasing baseline's batch size (and LR) or sequence length leads to worse evaluation results due to the training instability (case 1, 4, 7, 10, 13 in table). On the other hand, increasing batch size (and LR) or sequence length improves training efficiency, reducing the training time by up to 2.3x under the same number of training tokens (case 1, 4, 10, 13). Overall, this demonstrates the stability-efficiency dilemma for baseline pre-training: the training is more stable and can achieve better final generalization, but presumably with poorer training efficiency under smaller batch size/learning rate/sequence length; increasing them leads to better training efficiency, but with lower stability and worse generalization.

The correlation between instability and gradient variance outliers: For stochastic gradient optimization, when the gradient variance is large, the algorithm might spend much time bouncing around, leading to slower convergence and potential divergence [46]. Previous studies show that

Table 2: Zero-shot evaluation of the trained models on the WikiText-103 and LAMBADA datasets, following the evaluation methodology from [38]. Case 2 to 9 are compared with case 1, and case 11 to 17 are compared with case 10. Proposed work (SLW) and related works (16, 17) are discussed in Section 5.

	Case	Pre-training parameters	Training steps	Training tokens	Training time	WikiText PPL ↓	LAMBADA accuracy ↑
117M:	1: Baseline	bsz512-seqlen1K	300K	157B	37Hr	27.78	33.19%
	2: SLW 60K	bsz512-seqlen1K	200K	89B (1.8x)	20Hr (1.9x)	**27.74**	**34.78%**
	3: SLW 60K	bsz512-seqlen1K	330K	157B (1x)	33Hr (1.1x)	**27.01**	**34.41%**
	4: Baseline	bsz4K-seqlen1K	37.5K	157B (1x)	16Hr (2.3x)	28.09	32.54%
	5: SLW 30K	bsz4K-seqlen1K	37K	92B (1.7x)	10Hr (**3.7x**)	**27.77**	**33.40%**
	6: SLW 30K	bsz4K-seqlen1K	52.5K	157B (1x)	16Hr (2.3x)	**27.15**	**34.16%**
	7: Baseline	bsz512-seqlen2K	150K	157B (1x)	32Hr (1.2x)	28.19	32.99%
	8: SLW 110K	bsz512-seqlen2K	122.5K	71B (**2.2x**)	15Hr (2.5x)	**27.06**	**33.24%**
	9: SLW 110K	bsz512-seqlen2K	205K	157B (1x)	31Hr (1.2x)	**26.03**	**34.58%**
1.5B:	10: Baseline	bsz512-seqlen1K	300K	157B	341Hr	13.89	57.29%
	11: SLW 270K	bsz512-seqlen1K	360K	122B (1.3x)	286Hr (1.2x)	**13.89**	**57.38%**
	12: SLW 270K	bsz512-seqlen1K	428K	157B (1x)	364Hr (0.9x)	**13.88**	**57.89%**
	13: Baseline	bsz4K-seqlen1K	37.5K	157B (1x)	151Hr (2.3x)	14.76	55.06%
	14: SLW 45K	bsz4K-seqlen1K	50K	121B (1.3x)	121Hr (2.8x)	**13.88**	**58.20%**
	15: SLW 45K	bsz4K-seqlen1K	58.8K	157B (1x)	155Hr (2.2x)	**13.72**	**58.47%**
	16: Shortformer	bsz4K-seqlen1K	55K	157B (1x)	162Hr (2.1x)	14.14	57.23%
	17: Bsz Warmup	bsz4K-seqlen1K	58.8K	157B (1x)	165Hr (2.1x)	14.21	56.36%
Reference works:	18: Original GPT-2 117M [31], different data					37.50	45.99%
	19: Original GPT-2 1.5B [31], different data					17.48	63.24%
	20: Megatron-LM GPT-2 355M [31], same data					19.31	45.18%
	21: Megatron-LM GPT-2 2.5B [31], same data					12.76	61.73%

variance reduction methods improve training stability in areas such as reinforcement learning [22, 8, 1]. Figure 1(c), 1(d), 1(e) and 1(f) plot the l_1 norm and max element of Adam's variance state ($\sqrt{\boldsymbol{v}_t}$, where $\boldsymbol{v}_t = \beta_2 \boldsymbol{v}_{t-1} + (1-\beta_2)(\boldsymbol{g}_t)^2$)[4]. When baseline's batch size increases, the variance norm decreases but the max element increases. Comparing GPT-2 117M and 1.5B cases, larger model size leads to larger variance norm and max element. When sequence length increases for the GPT-2 117M case, the variance norm stays the same but the max element increases.

To further study the link between instability and gradient variance, Figure 1(g) and 1(h) plot the loss ratio (defined earlier in this section) and gradient variance norm/max element (all normalized by max value) for the most unstable 1.5B baseline with 4K batch size. Results show that when training loss spike happens and loss ratio increases, the gradient variance norm/max also increase (especially the max outliers). Table 3 presents the Pearson correlation coefficient calculations, which demonstrate a statistically significant positive correlation between loss ratio and gradient variance norm/max. Overall, our analysis shows that training instability has a strong correlation with gradient variance norm and (especially) max element outliers.

Length of early data sequences is critical to training stability: Aiming to solve the stability-efficiency dilemma we first tried traditional methods such as increasing gradient clipping, but it does not fully resolve the instability issue (Appendix A.2.2). Seeing that in Figure 1 the training instability mostly happens at the first half of training, we then explored whether we can solve the issue by gradually increasing any of the batch size/learning rate/sequence length during training. We already employed the same learning rate warmup mechanism used by existing GPT-2 and GPT-3 works [31, 38, 6]. We tried the batch size warmup method proposed in GPT-3 work [6], but the instability issue still appears when increasing the batch size (Section 5.1). Our investigation on the sequence length leads to interesting findings, where we find that sequence lengths play a critical role in training instability. Figure 2 presents the training loss curve of the most unstable GPT-2 1.5B pre-training with batch size 4K and seqlen 1K, together with another two artificial settings: one with seqlen 128, the other with mixed seqlen where we feed 900 steps of seqlen 128 then 100 steps of seqlen 1K in every 1K steps. The seqlen 128 case has no instability issue, even with large model size/batch size/learning rate. The mixed seqlen case has instability issues, and (1) they mostly happen when we switch to seqlen 1K (e.g., at step 900, 1900, 2900...); (2) they mostly happen during the first 5K steps, and after that it becomes more stable than the seqlen 1K case. These observations indicate that training instability is strongly correlated with early long sequence lengths, which motivates us to explore the sequence length warmup method described in the next section, and evaluations in Section 5 will demonstrate how this method provides a gradient variance reduction effect and solves the stability-efficiency dilemma.

[4]We use l_1 norm to avoid outlier amplification.

Table 3: Pearson correlation coefficient (with range (-1, 1)) between loss ratio and gradient variance norm/max. Low p-value indicates that the correlation is statistically significant.

	Pearson correlation coefficient	p-value
Loss ratio vs Gradient variance norm	0.23	0.0
Loss ratio vs Gradient variance max	0.26	0.0

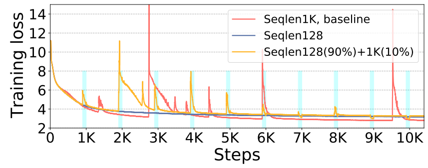


Figure 2: Step-wise training loss during GPT-2 1.5B pre-training (first 10K steps only) with batch size 4K, comparing seqlen 1K (baseline), seqlen 128, and mixed seqlen of 128+1K (1K seqlen used at the cyan areas).

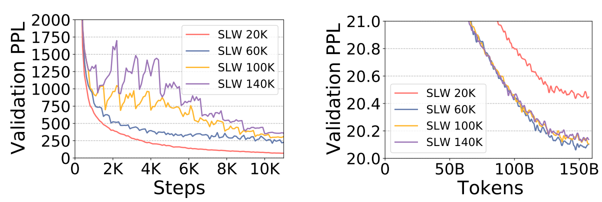
4 The Sequence Length Warmup Method

The analysis in last section about training instability and sequence lengths motivates us to explore sequence length warmup methods: the model needs to start learning with short sequence length for more stable training, then gradually increase the length when training becomes more stable so that the model can still learn from longer contextual information to achieve better final model accuracy.

The sequence length warmup strategy depends on two factors: how to support variable sequence length during training and how to adaptively decide the sequence length for each iteration (the pacing function). For the first component, we develop an efficient truncation-based implementation: For the baseline GPT-2 pre-training, the raw text inputs are indexed into sequences with the same length before training, so that the model can efficiently retrieve a batch of fixed-length sequences regardless of the actual sentence boundaries. It's possible to sort input data based on actual sequence lengths, but indexing the text based on all possible sequence lengths adds significant amount of overhead due to the massive pre-training data. To avoid the large indexing overhead, we take a lightweight approach: our implementation still lets the dataloader index the raw text into only the full sequence length. At each training step, our method uses pacing function to determine the sequence length and then truncates the full-length sequences to obtain a modified version of the mini-batch for training.

We define the pacing function as a step-wise linear function with the following properties: Given a starting sequence length $seqlen_s$, an ending sequence length $seqlen_e$ (full sequence length), and a total duration T (number of steps), the sequence length used for the training batch at step t is $seqlen_t = seqlen_s + (seqlen_e - seqlen_s) \times min(\frac{t}{T}, 1)$. Besides step-wise linear, we also explored 3 other pacing functions: i) We tried a discrete 2-stage pacing function from [28], but it leads to unstable training and worse convergence (Section 5.1). ii) We tried a step-wise root function ($seqlen_t = seqlen_s + (seqlen_e - seqlen_s) \times min((\frac{t}{T})^r, 1)$, where r is the root degree), which performs similar to linear but requires one extra hyperparameter. iii) We tried an adaptive pacing function based on training/validation losses, which also performs similar and requires extra tuning.

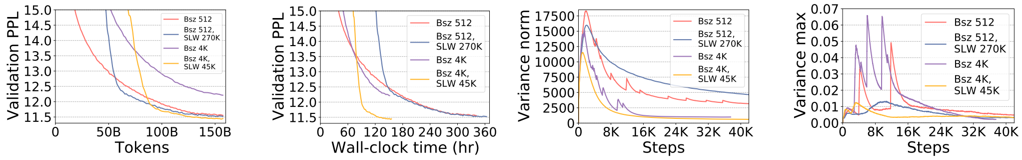
Pacing function analysis and tuning strategy: To study the impact of our approach's pacing function, we set the starting sequence length ($seqlen_s$) fixed at 8 and perform a grid search for the pacing function duration (T) on the GPT-2 117M case full training (details in Appendix A.3). We then choose the "best" duration based on the test data perplexity and zero-shot evaluation results after full training. All the cases have quite comparable evaluation results, indicating that the performance is not very sensitive to the duration T within a reasonable range. This grid search sheds light on a low-cost tuning strategy: we find that the best duration T is always the longest duration that does not have significant validation perplexity fluctuation during the first 10K steps (i.e., a few multiples of the LR warmup steps). In Figure 3(a) the SLW 60K is the longest duration we tested that does not have significant validation fluctuation during the first 10K steps. In Figure 3(b) and Appendix A.3 SLW 60K does provide the best final validation perplexity, best final test perplexity, and second best eval results. Since it does not require training the model until full convergence, this heuristic greatly reduces the hyperparameter tuning cost of our approach. Another grid search on the starting sequence length $seqlen_s$ shows that it's



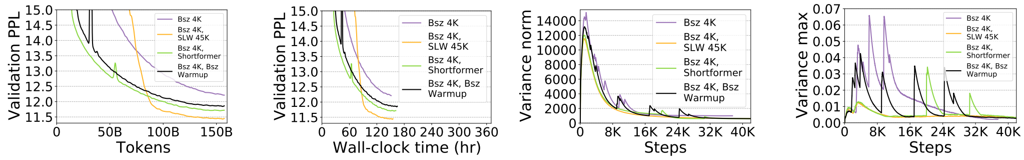
(a) Step-wise validation perplexity (beginning of training)

(b) Token-wise validation perplexity (end of training)

Figure 3: Validation perplexity during GPT-2 117M seqlen 1K pre-training with batch size 512 and different duration T. ("SLW 20K" means proposed approach with T=20K steps).



(a) Token-wise validation perplexity (b) Time-wise validation perplexity (c) Step-wise Adam variance norm (d) Step-wise Adam variance max element



(e) Token-wise validation perplexity (f) Time-wise validation perplexity (g) Step-wise Adam variance norm (h) Step-wise Adam variance max element

Figure 4: Validation perplexity and Adam variance norm/max element during GPT-2 1.5B seqlen 1K pre-training, comparing the baseline and proposed work (SLW) under different batch sizes/LR. Also compare with related works ("Shortformer" [28] and "Bsz Warmup" [6]) at 2nd row. Each row of subfigures share the same legend ("SLW 45K" means our work with T=45K steps).

generally better to set it as small as possible, to maximize the stability and convergence speedup benefit. However, if the validation perplexity has significant fluctuation near the starting sequence length, increasing $seqlen_s$ would lead to better convergence.

Overall, the low-cost tuning strategy can be summarized as: (1) Start with $seqlen_s = 8$ and $T =$ a few multiples of LR warmup steps. (2) Increase $seqlen_s$ until the validation perplexity no longer has significant fluctuation at the very beginning. (3) Perform a binary search to find the largest T that does not have significant validation perplexity fluctuation during the first few multiples of LR warmup steps. For the GPT-2 1.5B and GPT-3 125M models, we used this strategy to tune T and $seqlen_s$ for the pacing function, and results show that this low-cost tuning strategy could provide similar stability-efficiency benefit as grid search on full training runs (GPT-2 117M case).

5 Evaluation

5.1 GPT-2 experiments

For GPT-2 model, dataset, and hardware, we follow the same methodology in Section 3. For proposed work's pacing function configurations (Section 4), we use $seqlen_s = 8/64$ (for 117M/1.5B model based on tuning) and $seqlen_e = 1K/2K$ (full sequence length). To fully utilize the NVIDIA Tensor Core acceleration, we add a $seqlen_t = seqlen_t - (seqlen_t \bmod 8)$ postprocessing to make sure the sequence length is always a multiple of 8. For the total duration T, we tune this parameter (grid search for 117M and low-cost tuning for 1.5B) for each case. For the training parameters, for our approach we use the same shared parameters as the baseline except two parameters: 1) Because during sequence length warmup the number of tokens in a data batch is smaller, we modify the training termination condition so that all cases stop when reaching the same 157B training tokens. 2) Because of 1), proposed approach now has more training steps, which make it necessary to modify the learning rate decay schedule to have a fair comparison with the baseline. We change the learning rate decay to token-wise over the 157B tokens (still cosine decay) instead of step-wise over the total number of steps. We describe the underlying rationale in Appendix A.1.

Based on the following observations, we demonstrate that our approach resolves the dilemma and simultaneously improves the stability and efficiency. We will mainly present the GPT-2 1.5B results and leave some GPT-2 117M results in Appendix.

Significant stability gain: In Section 3 Table 1 we discussed how we measure the training instability based on the "loss ratio" metric, which shows that the baseline becomes less stable under larger model size/batch size/learning rate/sequence length. Comparing baseline and proposed work in this table shows that our work reduces this instability measurement to zero in all cases, together with max ratio close to 1.0 (no spike). This demonstrates the significant stability gain by our method.

Faster token-wise and time-wise convergence: Figure 4(a) and 4(b) present the validation perplexity curves during GPT-2 1.5B seqlen 1K pre-training, comparing baseline and our approach. When the batch size increases from 512 to 4K for baseline, the time-wise convergence becomes faster but the token-wise convergence becomes slower and poorer. On the other hand, our approach at batch size 4K provides faster and better convergence both token-wise and time-wise comparing with the best baseline curve in each case. Our approach with batch size 512 provides smaller convergence speedup because (1) Baseline with batch size 512 has less instability issue, limiting the gain from the proposed approach; (2) At batch size 512 the communication overhead is very high, and our approach takes more steps (i.e., communication rounds) than baseline to reach the same 157B training tokens. This extra communication cost "cancelled" part of the time saving from our approach. For GPT-2 117M, our approach provides similar token-wise and time-wise convergence speedup (Appendix A.3).

Advancing cost-quality Pareto curve: In Section 3 Table 2 we discussed about baseline's zero-shot evaluation results. For proposed work eval results in this table, we present them in two ways: one evaluated at the earliest checkpoint that provides better eval results than baseline (batch size 512 and seqlen 1K); the other one evaluated at the end of full training. Results show that our approach is able to advance the cost-quality Pareto curve in two ways: (1) To reach the same eval result quality as baseline, our approach reduces the required number of pre-training tokens and wall clock time by up to 2.2x and 3.7x, respectively; (2) Under the same 157B training tokens, our approach can further improve the eval result quality. In (1) the time-wise saving is higher than the token-wise because (a) For each Transformer block, the self-attention and intermediate layers have time complexity of $O(B \times L^2 \times H)$ and $O(B \times L \times H^2)$, respectively[5]. The proposed method uses shorter sequences at the beginning, reducing the time complexity *quadratically* for the self-attention sub-layer and linearly for the intermediate sub-layer of Transformer blocks; (b) By enabling stable training at larger batch size, our approach achieves additional time-wise saving by reducing the communication overhead.

Variance reduction helps stabilize training: In Section 3 we discussed the strong correlation between training instability and gradient variance norm/max. Figure 4(c) and 4(d) demonstrate that proposed approach stabilizes training and reduces both the Adam variance norm and the variance max element. Importantly, it avoids all the spikes of the variance max element, which all happen to be where the baseline training diverges. The shape of variance norm/max element shows that at the early stage of training when the amount of training data is much smaller than the model capacity, the model can easily overfit on the initial training data, causing extreme gradient variance and training instability. Our approach, beyond traditional curriculum learning, acts as a regularization method and reduces the overfitting at the early stage of training, which is also why it has slower convergence in first half of Figure 4(a). One may wonder why gradient clipping cannot help avoid these extreme gradient variance outliers. Although gradient clipping can avoid large gradient at every single step, it cannot avoid the gradient variance getting accumulated from multiple steps (Appendix A.2.2).

Comparing with related works: We now compare the proposed work with two related works on the most challenging "1.5B model + batch size 4K" case. The first work is the Shortformer where the first stage uses shorter sequences and the second stage uses full-length sequences [28]. Following the grid search in the paper, we use seqlen 128 for the first stage and set its duration at about half of the baseline duration (20K steps). The second work is the batch size warmup technique used by GPT-3 [6], where we set the starting batch size at 128 and then gradually increase it to 4K, and set the warmup duration same as the proposed work. Other training hyperparameters are unchanged. Figure 4(e) to 4(h) present the results. Both related works provide convergence speedup but it is less than our work. More importantly, they still have training instability issues. The Shortformer has an obvious training divergence at step 20K when the sequence length switches from 128 to 1K (the spike at 20K in Figure 4(h)). This shows when staying at the same shorter sequence length for too long, the model becomes heavily overfitted for that length which leads to divergence risk when/after switching to full length. Although both batch size warmup and our method reduce the number of tokens per batch in a similar fashion, batch size warmup does not provide any training stability benefit compared to the baseline. This indicates that providing the same number of shorter (simpler) sequences leads to better training stability than providing fewer number of same length (same difficulty) sequences. In addition, batch size warmup has a limitation that the batch size must be multiple of data-parallel size, which will be large for distributed training. On the other hand, for our method the sequence length only needs to be multiple of 8 to enable Tensor Core acceleration. Both related works provide non-zero "loss ratio" in Table 1 and worse zero-shot evaluation results in Table 2.

5.2 GPT-3 experiments

For experiments replicating the GPT-3 125M model [6] using *the Pile* public dataset [13], first we reproduce the original GPT-3 training recipe: 300B training tokens, seqlen 2K, batch size 256 with

[5] B, L, H represent batch size, sequence length, hidden size.

Table 4: Zero-shot evaluation of the trained GPT-3 125M models on 11 tasks used by the original GPT-3 work [6]. Per-task eval results in Appendix A.4.

Case	Batch size	Training tokens	Training time	Average accuracy ↑
1: Original [6]	256	300B		33.6
2: Baseline repro	256	300B (1x)	48Hr	31.4
3: Baseline 30x LR	2K	30B (10x)	6Hr (8x)	29.8 (95%)
4: SLW 40x LR	2K	30B (10x)	4Hr (12x)	31.1 (99%)

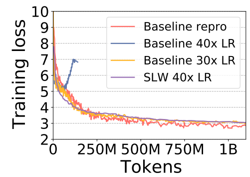


Figure 5: Training loss during GPT-3 125M pre-training (first 1B tokens).

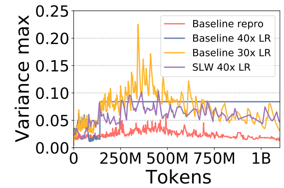


Figure 6: Gradient variance max during GPT-3 125M pre-training (first 1B tokens).

batch size warmup (start with 16 then gradually increase to 256 in first 4B tokens), learning rate 6×10^{-4} with a linear warmup of 375M tokens and a single cycle cosine decay over 260B tokens (6×10^{-5} min. learning rate)[6]. Then we explore an aggressive training scenario where only 30B tokens (10%) are allowed. This is because (1) GPT-3 paper admits that it has poor training sample efficiency and it sees much more text during pre-training than a human sees in the their lifetime [6, 21]. (2) There could exist cases where the total amount of data/computation resource is limited. We adjust several hyperparameters in this 30B-token training: 8x batch size (2K) for better training efficiency, learning rate decay reduced to 30B tokens (based on study that LR schedule should match total training tokens [14], warmup stays at 375M), min. learning rate reduced to 0 (based on recent study on GPT-3 [49]). For baseline we keep using 4B-token batch size warmup, but when our method is used ($seqlen_s = 72, T = 11.5K$ based on tuning) we disable it since both methods reduce tokens per batch. And for both cases we tune the learning rate and use the highest one that provides stable training, which is 30x (1.8×10^{-2}) for baseline and 40x (2.4×10^{-2}) for our method.

Figure 5 and 6 present the training loss and gradient variance max for the GPT-3 pre-training experiments. When applying 40x learning rate to the baseline (batch size warmup), it quickly diverges and cannot continue to train due to NaN losses. The corresponding gradient variance max element becomes a flat line after divergence because the gradients on all dimensions are so large that all gradients get clipped including the max element. After lowering the learning rate to 30x, the baseline is able to finish the whole training, but it can only retain 95% of average zero-shot accuracy on 11 tasks (HellaSwag [51], LAMBADA [26], TriviaQA [15], WebQs [3], Winogrande [36], PIQA [4], ARC Challenge/Easy [10], ANLI R1/R2/R3 [25]) compared with the case that reproduces the original GPT-3 training recipe[7] as shown in Table 4. In contrast, our approach enables stable training with 40x learning rate, demonstrates lower gradient variance max outliers than baseline with 30x learning rate, retains 99% of the original training recipe's average zero-shot accuracy, and achieves 10x data saving and 12x time saving. This demonstrates that the proposed method not only solves the stability-efficiency dilemma, but also opens a promising direction of significantly reducing total training cost in a different data efficiency dimension.

6 Conclusion

This paper presents the Sequence Length Warmup method, which solves a stability-efficiency dilemma inside GPT-style model pre-training, an critical issue that hinders efficient language model pre-training as explained in our in-depth analysis. By enabling stable training on more aggressive training recipe, this method also motivates a new dimension of training cost reduction by improving the data efficiency, as demonstrated by the 10x data and 12x time saving in our GPT-3 experiments. We believe that the effectiveness, simplicity, and easy-to-use/tune make the proposed method a must-try for deep learning practitioners, and we hope this work could motivate more studies on improving training data efficiency.

[6] Different from GPT-2, GPT-3 uses token-based learning rate schedule and we follow it. The GPT-3 experiments are also performed on 128 V100 GPUs but in a different cluster with faster network, thus the training time is not directly comparable with GPT-2 results.

[7] Our reproduced GPT-3 has 2.2 point lower average accuracy than the original GPT-3, which is because of the different training data and OpenAI employed many data processing techniques [6]

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] In conclusion we point out that our work is just one way of improving data efficiency, and needs future work to further reduce data requirement.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We open sourced the code in a deep learning optimization library (name hidden to maintain anonymity), and Section 3 and 5 include all instructions needed to reproduce the experiments.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Section 3 and 5 include all the training details.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [N/A] Our results are based on a single seed given the pre-training is expensive.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Section 3 and 5 include the information.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]

(b) Did you mention the license of the assets? [N/A]

(c) Did you include any new assets either in the supplemental material or as a URL? [N/A] We open sourced the code in a deep learning optimization library (name hidden to maintain anonymity), but it's difficult to provide an anonymized version of the code during submission.

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]