Curriculum Learning: A Regularization Method for Efficient and Stable Billion-Scale GPT Model Pre-Training

Conglong Li, Minjia Zhang, Yuxiong He

Abstract

Recent works have demonstrated great success in training large autoregressive language models (e.g., GPT-3) on unlabeled text corpus for text generation. To reduce their expensive training cost, practitioners attempt to increase the batch sizes and learning rates. However, increasing them often cause training instabilities and poor generalization. On the other side, using smaller batch sizes or learning rates would reduce the training efficiency, significantly increasing training time and cost. We investigate this stability-efficiency dilemma and identify that long sequence length is one of the main causes of training instability in large-scale GPT model pre-training.

Based on our analysis, we present a novel sequence length warmup method that simultaneously improves training stability and efficiency. As a kind of curriculum learning approach, our method improves the training convergence speed of autoregressive models. More importantly, our in-depth analysis shows that our method exerts a gradient variance reduction effect and regularizes early stages of training where the amount of training data is much smaller than the model capacity. This enables stable training with much larger batch sizes and learning rates, further improving the training speed. Evaluations show that our approach enables stable GPT-2 (117M and 1.5B) pre-training with 8x larger batch size and 4x larger learning rate, whereas the baseline approach struggles with training instability. Despite achieving remarkable model accuracy, pre-training GPT models raises huge challenges on training efficiency and instability. To achieve the same or better zero-shot WikiText-103/LAMBADA evaluation results, our approach reduces the required number of pre-training tokens and wall clock time by up to 55% and 73%, respectively.

1. Introduction

Large-scale Transformer-based language models have powered breakthroughs in many natural language processing tasks (Vaswani et al., 2017; Devlin et al., 2019). These models are first pre-trained with massive open-domain web text corpus and then knowledge-transferred to domain-specific tasks. There has been many explorations in designing the unsupervised pre-training strategy, e.g., masked language modeling (Devlin et al., 2019; Liu et al., 2019), causal language modeling (Radford et al., 2018a;b), and unified language modeling (Dong et al., 2019). Among them, one of the most representative cases is the GPT family, which has shown outstanding performance in sentence generation and promising results on zero/few-shot evaluation on downstream tasks.

Despite achieving remarkable model accuracy, pre-training GPT models raises huge challenges on training efficiency and instability. On the efficiency side, since the size of GPT models continues to grow from a few hundreds millions of parameters such as GPT (110M parameters) (Radford et al., 2018a), to GPT-2 (1.5B) (Radford et al., 2018b) and to 175B GPT-3 (Brown et al., 2020), the training cost also increases significantly. For example, it requires approximately 9.2 days on 512 V100 GPUs to train a 8.3B GPT-2 (Shoeybi et al., 2019), and 47.8 days on 2240 A100 GPUs to train a 530B GPT-3-style MT-NLG model (Microsoft & Nvidia, 2021). To reduce the training wall clock time of these large models, one common solution is to employ distributed training with a massive number of GPUs such that the model can finish training with a much faster time-wise speed. Furthermore, increasing the batch size increases the computation-vs-communication ratio, improving the overall hardware utilization efficiency.

Despite increased training throughput and efficiency, increasing the batch size is not always the panacea. In fact, the common practice often resorts to using smaller batch sizes (e.g., up to 1.6K for GPT-3) despite it would adversely affect training efficiency. This is because a too large batch size can make training more difficult, e.g., causing training instability that leads to divergence or slow convergence, which can lead to wasted training effort. To investigate the interplay between batch sizes and training stability, we conduct a thorough study of the GPT-2 pre-training task (Radford et al., 2018b).
et al., 2018b; Shoeybi et al., 2019) with different models sizes, batch sizes, learning rates, and sequence lengths. We find that increasing one or some of them often increases the likelihood of training instability and divergence. Even if the training does not fully diverge, the training instability often leads to worse convergence that hurts final model accuracy. We also find that existing techniques like extra gradient clipping and batch size warmup (Brown et al., 2020) cannot easily solve this issue.

To address the above training efficiency-stability dilemma, our analysis shows that the sequence length at the early stages of training plays a critical role. The first half of pre-training has a higher probability of having instability issue under large model size, batch size, and learning rate. However, using 8x shorter sequence length makes the training stable again, at the cost of shorter contextual information to learn from. Based on this finding, we propose a novel sequence length warmup method, which starts training with short sequences and gradually increases the length. Our method can be viewed as a kind of curriculum learning (CL) (Bengio et al., 2009), which presents easier/simpler examples earlier during training and gradually increases the sample difficulties. Unlike traditional CL, which was proposed to solely improve training convergence speed, we focus on using adaptive sequence length to overcome the training stability-efficiency dilemma. Moreover, although CL was explored and verified for NLP one-stage and fine-tuning tasks (Platanios et al., 2019; Xu et al., 2020), its application to pre-training GPT models is not well studied. We find that our sequence length warmup method, like existing CL works, could improve the convergence speed under the same training hyperparameters.

Interestingly and more importantly, we find that our approach enables stable and efficient training with much larger batch sizes and learning rates than baseline approaches. Our in-depth analysis shows that our approach’s better training stability lies in its gradient variance reduction effect: During the early stages of training where the amount of training data is much smaller than the model capacity, the gradient variance is usually larger. Although the gradient variance is generally reduced under larger batch size, the largest variance on certain dimensions (i.e., the outliers) is increased and it reaches extreme values when training divergence happens. Using Adam optimizer’s variance state, we observe that our approach helps reduce both the norm of this variance and the maximum variance outliers. This variance reduction effect helps our approach to regularize the early stages of training and achieve stable large-batch training without hurting the token-wise convergence speed and final generalization accuracy.

We implement this sequence length warmup method and apply it to the GPT-2 pre-training with up to 1.5B parameters. Evaluations show that our approach enables stable and efficient training with 8x larger batch size and 4x larger learning rate, while the baseline and relate works struggle with instability under the same settings. To achieve the same validation perplexity targets during pre-training, our approach reduces the required number of tokens and wall clock time by up to 61% and 57%, respectively. To achieve the same or better zero-shot WikiText-103/LAMBADA evaluation results at the end of pre-training, our approach reduces the required number of tokens and wall clock time by up to 55% and 73%, respectively. We also study the impact of the sequence length warmup schedule and identify a lightweight hyperparameter tuning strategy for our approach, which only incurs a small fraction of tuning cost compared to the total pre-training cost.

We make the following contributions: i) We conduct an extensive study of the GPT-2 pre-training task, which provides detailed insights about the training stability-efficiency dilemma that motivate our work (Section 3). ii) Based on further study about sequence length, we present a novel sequence length warmup method for GPT-2 model (and autoregressive model in general), which is both efficient and easy to integrate (Section 4). iii) We conduct large-scale experiments to demonstrate the proposed work’s ability to provide superior training stability and efficiency at the same time, and how it achieves the improvements by reducing gradient variance and regularizing training. To the best of our knowledge, we are the first work to demonstrate the benefit of curriculum learning as a regularization method that improves training stability and efficiency simultaneously (Section 5). iv) The implementation of our approach as well as the necessary changes to the GPT-2 pre-training framework has been open sourced in a deep learning optimization library called DeepSpeed.

2. Language Model Pre-training Background

The accuracy of transformer-based language models grows substantially with its model size (Radford et al., 2018a;b; Brown et al., 2020). Today, a large language model such as GPT-3 (Brown et al., 2020) contains up to 175B parameters, and recent studies show that model accuracy can continue to improve with even larger model sizes (Kaplan et al., 2020). However, training these large models often incurs excessively long training time and training difficulties (Brown et al., 2020). 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 (Tang et al., 2021) have studied gradient compression and demonstrate their effectiveness against auto-encoding models such as BERT (Devlin et al., 2019). An alternative approach to alleviate these overheads is to use large batch sizes. For example, LAMB (You et al., 2020) and 1-bit LAMB (Li et al., 2021) 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 such as T5, Raffel et al. (2020) use batch size up to 2K (for sequence length 512, i.e., 1M tokens per batch). For autoregressive models such as the GPT family (Radford et al., 2018a;b; Brown et al., 2020), 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 (Wolf, 2021).

3. Motivation and Insights

In this section we perform an in-depth analysis of the GPT-2 model pre-training baseline (without our method). We follow the training pipeline from the NVIDIA Megatron-LM work (Shoeybi et al., 2019)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 (Radford et al., 2018b): 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 (Devlin et al., 2019), CC-Stories (Trinh & Le, 2018), RealNews (Zellers et al., 2019), and OpenWebtext (Radford et al., 2019).

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 $1.5 \times 10^{-4}$ with a linear warmup of 3K steps and a single cycle cosine decay over the remaining 297K steps ($1 \times 10^{-5}$ min. learning rate). The second parameter set tests a more aggressive training strategy: batch size 4K (8× larger), 37.5K total training steps (157B tokens)3, and learning rate $6 \times 10^{-4}$

2https://github.com/NVIDIA/Megatron-LM
3For pre-training it is common to keep the number of training tokens the same for fair comparison.
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Table 2. Zero-shot evaluation of the trained models on the WikiText-103 and LAMBADA datasets, following the evaluation methodology from (Shoeybi et al., 2019). Case 2 to 9 are compared with case 1, and case 11 to 17 are compared with case 10. Proposed work (CL) and related works (last two rows) are discussed in Section 5.

| Case | Pre-training parameters | Pre-training steps, tokens, time | WikiText perplexity \(\downarrow\) | LAMBADA accuracy \(\uparrow\) |
|------|-------------------------|----------------------------------|-----------------|-----------------|
| 117M: | 1: Baseline bsz512-seqlen1K | 300K, 157B, 37Hr | 27.78 | 33.19% |
|      | 2: CL 60K bsz512-seqlen1K | 200K, 89B (-43%), 20Hr (-46%) | 27.74 | 34.78% |
|      | 3: CL 60K bsz512-seqlen1K | 330K, 157B (-11%), 33Hr | 27.01 | 34.41% |
|      | 4: Baseline bsz4K-seqlen1K | 37.5K, 157B (-1%), 1Hr (57%) | 28.09 | 32.54% |
|      | 5: CL 30K bsz4K-seqlen1K | 37K, 92B (-41%), 10Hr (73%) | 27.77 | 33.40% |
|      | 6: CL 30K bsz4K-seqlen1K | 52.5K, 157B (-16%), 16Hr (57%) | 27.15 | 34.16% |
|      | 7: Baseline bsz5T2-seqlen2K | 150K, 157B (-1%), 32Hr (14%) | 28.19 | 32.99% |
|      | 8: CL 110K bsz512-seqlen2K | 122.5K, 71B (-55%), 15Hr (-59%) | 27.06 | 33.24% |
|      | 9: CL 110K bsz512-seqlen2K | 205K, 157B (-16%), 31Hr | 26.03 | 34.58% |
| 1.5B: | 10: Baseline bsz512-seqlen1K | 300K, 137B, 341Hr | 13.89 | 57.29% |
|      | 11: CL 270K bsz512-seqlen1K | 360K, 122B (-22%), 286Hr (-16%) | 13.89 | 57.38% |
|      | 12: CL 270K bsz512-seqlen1K | 428K, 157B (-7%), 364Hr (7%) | 13.88 | 57.89% |
|      | 13: Baseline bsz4K-seqlen1K | 37.5K, 157B (-7%), 15Hr (56%) | 14.76 | 35.06% |
|      | 14: CL 45K bsz4K-seqlen1K | 50K, 121B (-23%), 121Hr (-65%) | 13.88 | 58.20% |
|      | 15: CL 45K bsz4K-seqlen1K | 58.8K, 157B (-55%), 155Hr (-55%) | 13.72 | 58.47% |
|      | 16: 2-stage CL 20K bsz4K-seqlen1K | 55K, 157B (-52%), 162Hr (-52%) | 14.14 | 57.23% |
|      | 17: Bsz Warmup 45K bsz4K-seqlen1K | 58.8K, 157B (-52%), 165Hr (-52%) | 14.21 | 56.36% |

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.

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.

Training instability are undesirable because (1) it could lead to divergence that never recover (Wolf, 2021); (2) in our 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 57% under the same number of training tokens. 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. In the next section we show that the sequence length at early stages of training plays a critical role about this dilemma, and describe how we design and implement sequence length warmup method that resolves this dilemma for the GPT-2 model pre-training task.

4. Analysis and Design

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 (Radford et al., 2018b; Shoeybi et al., 2019; Brown et al., 2020). We tried the batch size warmup method proposed in GPT-3 work (Brown et al., 2020), but the instability issue still appears when increasing the batch size (Section 5.3). Our investigation on the sequence length leads to interesting findings, where we find that sequence lengths play a critical role in training instability based on the analysis below.

Figure 2 presents the training loss curve of GPT-2 1.5B pre-training with batch size 4K and seqlen 1K (the most unstable baseline in last section), 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, 1800, 2700...); (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 long sequence lengths and motivate us to explore sequence length warmup methods: the model needs to start learning with short sequence length for more stable training, and 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 (1K or 2K). 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_1, an ending sequence length seqlen_2 (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_1 + (seqlen_2 − seqlen_1) × min((t/T)^r, 1). Besides step-wise linear, we also explored 3 other pacing functions: i) We tried a discrete 2-stage pacing function from (Press et al., 2020), but it leads to unstable training and worse convergence (Section 5.3). ii) We tried a step-wise root function (seqlen_t = seqlen_1 + (seqlen_2 − seqlen_1) × min((t mod 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.

The proposed sequence length warmup method can be viewed as a kind of curriculum learning (CL) scheme, which was initially proposed to improve training convergence speed by presenting easier/simpler examples earlier during training and gradually increasing the sample difficulties (Bengio et al. (2009)), broader related works discussed in Section 6). The shorter sequences are not necessarily easier but can be viewed as simpler examples since there are less context to encode.

5. Evaluation

Methodology For model, dataset, and hardware, we follow the same methodology in Section 3. For proposed work’s pacing function configurations (defined in Section 4), we use seqlen_1 = 8/64 (for 117M/1.5B model) and seqlen_2 = 1K/2K (i.e., the full sequence length). To fully utilize the Tensor Core acceleration in NVIDIA V100 GPU, we add a seqlen_t = seqlen_t − (seqlen_t mod 8) post-processing to make sure the sequence length is always a multiple of 8. For the total duration T, we tune this parameter and use different numbers for each case. Our analysis shows that there exists a low-cost tuning strategy for T and seqlen_1 (Section 5.4). For the training parameters, for our approach we use the same shared parameters as the baseline in Section 3 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 have more training steps, which makes 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.

5.1. Our work resolves stability-efficiency dilemma

As discussed in Section 3, baseline suffers from the stability-efficiency dilemma. 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 quantitatively 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 3(a) and 3(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-wise saving from our approach. For GPT-2 117M, our approach provides similar token-wise and time-wise convergence speedup (Appendix A.3).

To quantitatively measure the speedup, Table 3 summarizes the required number of tokens and training time for baseline and our approach to reach the same validation perplexity (comparing under the same batch size). Results show that our approach reduces the required number of tokens and training time by up to 45% and 41%, respectively. In addition, proposed work achieves validation perplexity that baseline is unable to achieve during the whole training. For GPT-2 117M, our approach reduces the required number of tokens and training time by up to 61% and 57%, respectively (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 sequence length 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 55% and 73%, respectively; (2) Under the same amount of 157B training tokens, our approach can further improve the eval result quality than (1). 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. 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

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To return the natural text as a plain text representation, the provided content seems to be a continuation of a larger text, possibly discussing the results of experiments in a scientific context, focusing on token and time efficiency improvements across different batch sizes. The text includes figures and tables that appear to summarize experimental results, comparing baseline and proposed methods, focusing on validation perplexity (PPL), Adam variance norm, and other metrics across different batch sizes and training times. The content also touches upon theoretical underpinnings, such as the complexity of different layers in Transformers and how these complexities affect training outcomes.

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4 $B$, $L$, $H$ represent batch size, sequence length, hidden size.
5.2. Variance reduction helps stabilize training.

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 (Wang et al., 2013). Previous studies show that variance reduction methods improve training stability in areas such as reinforcement learning (Mao et al., 2018; Cheng et al., 2019; Anschel et al., 2017). One surprising finding about proposed work is that it can, in addition to the well-known benefit of faster convergence speed by curriculum learning, help to reduce the gradient variance norm/max element, which is presumably why it leads to much more stable training. Figure 3(c) and 3(d) plot the $l_1$ norm and max element of Adam’s variance state ($\sqrt{v_t}$, where $v_t = \beta_2 v_{t-1} + (1 - \beta_2)(g_t)^2$) for the GPT-2 1.5B case\(^3\). (Appendix A.3 contains GPT-2 117M case results). 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. These demonstrate that large gradient variance norm/max element is one of the symptoms of the training instability issue, similar to what was observed in the aforementioned studies in reinforcement learning area. We find 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 3(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).

5.3. 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 “2-stage curriculum learning” where the first stage uses shorter sequences and the second stage uses full-length sequences (Press et al., 2020). Following the tuning strategy in the paper, we use sequence length 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 pre-training where the training starts with a smaller batch size (sequence length unchanged) and gradually increases to full batch size (Brown et al., 2020). In our experiment, we set the starting batch size at 128 and then gradually increase it to 4K, and set the warmup duration at 45K steps (same as the proposed work). Other training hyperparameters are unchanged.

Figure 3(e) to 3(h) present the validation perplexity and Adam variance norm/max element, comparing baseline, proposed work, and related works. Both related works provide convergence speedup but it is less than our work. More importantly, they still have training instability issues. The 2-stage CL has an obvious training divergence at step 20K when the sequence length switches from 128 to 1K (the spike at 20K in Figure 3(h)). This is because 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.

5.4. Pacing function analysis and tuning strategy

To study the impact of our approach’s pacing function, we set the starting sequence length ($seqlen_1$) fixed at 8 and perform a grid search for the pacing function duration ($T$ in Section 4) on the 117M case full training (Appendix A.3 includes result details). We then choose the “best” duration based on the test data perplexity and zero-shot evaluation results after 157B-token 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.

\(^3\)We plot them step-wise since the optimization are performed step-wise, and use $l_1$ norm to avoid outlier amplification.
In the NLP area, most of the curriculum learning works focus on small-scale one-stage tasks and downstream fine-tuning tasks, such as neural machine translation (NMT) (Kocmi & Bojar, 2017; Bojar et al., 2017; Zhang et al., 2018; Platanios et al., 2019; Zhang et al., 2019) and natural language understanding (NLU) (Sachan & Xing, 2016; 2018; Tay et al., 2019; Xu et al., 2020). These works show that curriculum learning can improve convergence speed, reduce training time, and improve accuracy under the same training hyperparameters as baseline. Only a few works explore curriculum learning for language model pre-training. Press et al. (2020) apply curriculum learning to neural language modeling pre-training, specifically a transformer model with 247M parameters (Baevski & Auli, 2018). They find that by adding an additional first training stage with a shorter sequence length, it is possible to achieve the same dev. set perplexity with shorter total training time. Zhang et al. (2021) apply curriculum learning to BERT-base pre-training, a transformer model with 110M parameters. They find that by grouping sequences with similar length and with curriculum learning, it is possible to achieve similar downstream task accuracy with shorter pre-training time. Campos (2021) apply curriculum learning to ELMo pre-training, a bi-directional LSTM model with 93.6M parameters (Peters et al., 2018). They test a variety of curricula on the WikiText-2 and WikiText-103 but do not find strong evidence that the use of curriculum learning can improve language model pre-training.

Overall, a general low-cost tuning strategy can be summarized as: (1) Start with $\text{seqlen}_1 = 8$ and $T = 1$ or a few multiples of LR warmup steps. (2) Increase $\text{seqlen}_1$ 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 1.5B model, we used this strategy to tune $T$ and $\text{seqlen}_1$ for the pacing function. Results show that this low-cost tuning strategy (1.5B case) could provide similar stability-efficiency benefit as grid search on full training runs (117M case).

### 6. Curriculum Learning Related Work

Inspired by how humans and animals are trained, curriculum learning aims to improve machine learning model training convergence speed by presenting easier/simpler examples earlier during training (Elman, 1993; Sanger, 1994; Bengio et al., 2009). Previous studies have demonstrated the benefit of faster convergence speed by curriculum learning in many domains such as natural language processing (NLP), computer vision, and neural evolutionary computing. In this section we will discuss recent related works in the NLP area. Recent survey papers include a more complete literature review (Wang et al., 2020; Soviany et al., 2021).

In the NLP area, most of the curriculum learning works...
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As discussed in main paper Section 5 methodology, proposed approach needs more training steps than baseline in order to reach the same 157B training tokens. This makes it necessary to modify the learning rate decay schedule for proposed approach. We first tried to increase the number of learning rate decay steps by half of the proposed approach’s pacing function duration $T$ (since the proposed approach roughly needs $T/2$ additional steps to reach 157B tokens). However, we find that simply increasing decay steps still leads to faster learning rate decay than baseline. At last we change the learning rate decay to token-wise (same cosine decay over the 157B tokens) instead of step-wise. This is because for the proposed approach there are fewer tokens per step at the beginning. So even if we increase the LR decay steps, it still cannot avoid decaying faster token-wise at the beginning compared to baseline. As shown in Figure 5, the proposed approach with step-wise LR decay (with $T/2$ extra decay steps) has faster LR decay token-wise compared to baseline, which leads to a worse validation perplexity curve. On the other hand, the same proposed approach case with token-wise LR decay has the same token-wise LR decay schedule as baseline, which leads to better convergence.

A.2. Additional analysis about training hyperparameters

In main paper Section 5.4 we demonstrate that proposed approach’s two hyperparameters can be tuned with very low cost only running the very beginning of the training (the third hyperparameter, ending sequence length, does not require tuning since it will always be the full length). To understand more about how proposed approach affects the choice and tuning of normal training hyperparameters, this section provides additional analysis about learning rates and gradient clipping. Results demonstrate that (a) Compared to baseline, proposed approach requires less tuning effort on these hyperparameters to provide a stable training; (b) By enabling stable training on larger learning rates, proposed approach could provide better training efficiency and convergence (as demonstrated in main paper Section 5); (c) Tuning gradient clipping for baseline could not provide the same training stability as proposed approach.

A.2.1. Learning rate

In Section 5 we demonstrate that proposed approach can provide stable and more efficient training at larger batch size and learning rate, where baseline suffers from training instability. We increased both batch size and learning rate at the same time because (a) Large-batch training is more efficient for large-scale distributed training, so larger batch was necessary in our study (b) In order to maintain the same convergence speed, it is necessary to simultaneously increase the learning rate under larger batch size. A well-known rule of thumb is that the learning rate should at least increase by the square root of the batch size’s increase ratio.

As a controlled experiment, here we perform additional studies about what if we keep the batch size the same and only tune learning rate for baseline and proposed approach. We do not consider the case of “same learning rate, different batch sizes” due to the reason (b) above. Table 4 presents the number of steps with training loss ratios (defined in main paper Section 3 as an indicative measurement of training instability) larger than 1.5 during GPT-2 1.5B seqlen 1K pre-training (first 3K steps only) with batch size 2K\(^6\), 5 different seeds, and different learning rates for baseline and proposed approach. And Figure 6 illustrates some

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**Figure 5.** Validation perplexity and learning rate during GPT-2 1.5B seqlen 1K pre-training with batch size 512, comparing the baseline and proposed approach under different learning rate decay schedules. All subfigures share the same legend (“CL 270K” means proposed approach with $T=270K$ steps).

**Figure 6.** Step-wise training loss during GPT-2 1.5B seqlen 1K pre-training (first 3K steps only) with batch size 2K, different learning rates for baseline and proposed approach (“CL 8K” means proposed approach with $T=8K$ steps).
Table 4. Number of steps with training loss ratios (defined in Section 3) larger than 1.5 during GPT-2 1.5B seqlen 1K pre-training (first 3K steps only) with batch size 2K, 5 different seeds, and different learning rates for baseline and proposed approach (CL). Left/right number in each cell is for baseline/CL, respectively.

| Seed         | Baseline #loss ratio > 1.5 | LR = 1.5 × 10⁻⁴ | LR = 3 × 10⁻⁴ | LR = 6 × 10⁻⁴ | LR = 12 × 10⁻⁴ |
|--------------|----------------------------|-----------------|---------------|---------------|----------------|
| Seed 1234    | 0/0                        | 296/0           | 339/0         | 179/74        |                |
| Seed 1235    | 0/0                        | 302/0           | 408/0         | 555/459       |                |
| Seed 1236    | 0/0                        | 0/0             | 569/0         | 626/414       |                |
| Seed 1237    | 7/0                        | 0/0             | 548/0         | 614/139       |                |
| Seed 1238    | 0/0                        | 0/0             | 121/0         | 394/29        |                |
| Total        | 7/0                        | 598/0           | 2005/0        | 2368/1115     |                |

of the cases with seed 1236 to show how the loss spikes look like. Results show that proposed approach provides stable training during this first 3K steps for all five seeds at learning rates up to $6 \times 10^{-4}$, while baseline with seed 1237 still has 7 large loss ratios at learning rate as low as $1.5 \times 10^{-4}$. At learning rate $12 \times 10^{-4}$ both cases have large loss ratios, but proposed approach reduces the frequency by 2.1x. This demonstrates that (a) Larger learning rates lead to higher training instability risk for both cases. (b) With the same amount of tuning effort, proposed approach has a higher probability of providing a stable training because of the wider range of learning rates it enables; (c) Since proposed approach enables stable training at larger learning rate, it could provide better and faster training convergence as shown in main paper Section 5.

A.2.2. Gradient clipping

In main paper Section 5 we used gradient clipping at 1.0 (global gradient $l_2$ norm is clipped to 1.0) following the previous work (Shoeybi et al., 2019). Here we perform additional studies about what if we apply more gradient clipping to baseline. Figure 7(a) presents the training loss during GPT-2 1.5B seqlen 1K pre-training (first 5K steps only) with batch size 4K (the same hyperparameters as the second set in Section 3), comparing the baseline and proposed approach under different gradient clipping levels.

Results show that when applying more gradient clipping to baseline, the training has less and smaller loss spikes. And the Adam variance norm is also reduced as shown in Figure 7(c).

However, more gradient clipping does not fully resolve the training instability issue. Even baseline with the lowest gradient clipping norm cannot avoid all training loss spikes, while proposed approach with default gradient clipping has no loss spike. As described in main paper end of Section 5.2, we believe that this is a limitation of common gradient clipping technique: Although gradient clipping can avoid too large gradient at every single step, it cannot avoid the gradient variance getting accumulated at certain dimensions (as shown in Figure 7(d)), especially for large batch sizes. Another concern about applying more gradient clipping is that the momentum norm is also reduced due to more clipping (Figure 7(b)). This indicates that when later the training reaches a more stable stage, more gradient clipping could hurt the convergence speed. On the other hand, proposed approach will not affect the convergence speed after the full sequence length is reached. Another thing to note is that proposed approach relies less on gradient clipping: at gradient clipping norm 1.0, baseline has 798 clippings in the first 5K steps while proposed approach has 628 clippings (21% less).

Overall, this analysis demonstrates that proposed approach requires less or no tuning on gradient clipping, while baseline still has training stability issue with more gradient clipping. It is possible that more complex and adaptive gradient/variance/activation clipping techniques could potentially achieve the same level of training stability as proposed approach. However, inventing and applying such techniques would require an effort no lower than the proposed approach, which is both easy to integrate and low-cost to tune.

A.3. GPT-2 117M evaluation results

Figure 8 presents the validation perplexity and Adam variance norm/max element during GPT-2 117M pre-training, comparing the baseline and proposed work (CL) under different batch sizes/LR and sequence lengths. Table 5 presents number of tokens and wall clock time to reach the same validation perplexity during GPT-2 117M pre-training, comparing the baseline and proposed work under different batch sizes/LR and sequence lengths. Table 6 presents the zero-shot evaluation of the trained 117M models on the WikiText-103 and LAMBADA datasets for baseline and proposed work with different pacing function duration.

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7We also tried less than 0.25 gradient clipping, which triggered a silent crash without error messages after around 100 steps. We did not have enough time to find the root cause, but it could be caused by the too extreme gradient clipping.
Figure 7. Training loss, Adam momentum $l_1$ norm, and Adam variance $l_1$ norm/max element during GPT-2 1.5B seqlen 1K pre-training (first 5K steps only) with batch size 4K, comparing the baseline and proposed approach under different gradient clipping levels. Grad clip 1.0 indicates that the global gradient $l_2$ norm is clipped to 1.0. All subfigures share the same legend as 7(d) (“CL 45K” means proposed approach with $T=45K$ steps).

Figure 8. Validation perplexity and Adam variance norm/max element during GPT-2 117M pre-training, comparing the baseline and proposed work (CL) under different batch sizes/LR and sequence lengths. Each row of subfigures share the same legend (“CL 60K” means proposed work with $T=60K$ steps).
Table 5. Number of tokens (Billion) and wall clock time (Hour) to reach the same validation perplexity during GPT-2 117M pre-training, comparing the baseline and proposed work under different batch sizes/LR and sequence lengths. Last two rows use the best PPL achieved by baseline and CL as the target.

| Vali Bsz 512, Seqlen 1K | Bsz 4K, Seqlen 1K | Bsz 512, Seqlen 2K |
|-------------------------|------------------|------------------|
| PPL Target              | Num. tokens / Wall time | Num. tokens / Wall time | Num. tokens / Wall time |
| 21.5                    | 69.0B / 35.5B (-48%) | 10.31B / 6.41B (-38%) | 102.55B / 52.16B (-49%) |
|                         | 16.28Hr / 8.95Hr (-45%) | 14.96Hr / 11.7Hr (-22%) | 14.96Hr / 11.94Hr (-43%) |
| 16.28                     | 100.41B / 59.21B (-40%) | 102.55B / 52.16B (-49%) | 14.96Hr / 11.94Hr (-43%) |
| 21.5-20K                 | 73.4B / 50.87B (-31%) | 73.4B / 50.87B (-31%) | 73.4B / 50.87B (-31%) |
| 22.84                     | 13.71Hr / 6.91Hr (-50%) | 13.71Hr / 6.91Hr (-50%) | 13.71Hr / 6.91Hr (-50%) |
| 22.84-34.60%             | Did not reach / 136.47B | Did not reach / 148.06B | Did not reach / 135.58B |
| Vali PPL = 20.38         | Did not reach / 29.17Hr | Did not reach / 15.27Hr | Did not reach / 27.42Hr |
| Baseline Vali PPL = 20.38| 135.63B / 84.1B (-38%) | 156.87B / 68.79B (-56%) | 143.34B / 55.5B (-61%) |
| Baseline Vali PPL = 20.38| 15.32Hr / 8.51Hr (-38%) | 13.91Hr / 6.58Hr (-55%) | 29.23Hr / 12.58Hr (-57%) |
| Baseline Vali PPL = 20.38| 19.64B / 9.91B (-45%) | 19.64B / 9.91B (-45%) | 19.64B / 9.91B (-45%) |
| Baseline Vali PPL = 20.38| 20.99Hr / 11.94Hr (-43%) | 20.99Hr / 11.94Hr (-43%) | 20.99Hr / 11.94Hr (-43%) |

Table 6. Zero-shot evaluation of the trained 117M models on the WikiText-103 and LAMBADA datasets, following the evaluation methodology from (Shoeybi et al., 2019).

| Case | Pre-training parameters | Pre-training steps, tokens, time | Pre-training test perplexity ↓ | WikiText-103 perplexity ↓ | LAMBADA accuracy ↑ |
|------|-------------------------|---------------------------------|--------------------------------|--------------------------|-------------------|
| 1: Baseline | bsz512-seqlen1K | 300K, 157B, 37Hr | 20.75 | 27.78 | 33.19% |
| 2: CL 20K | bsz512-seqlen1K | 310K, 157B, 30Hr | 20.49 | 27.43 | 34.60% |
| 3: CL 60K | bsz512-seqlen1K | 350K, 157B, 33Hr | 20.11 | 27.01 | 34.41% |
| 4: CL 100K | bsz512-seqlen1K | 370K, 157B, 35Hr | 20.16 | 26.91 | 34.21% |
| 5: CL 140K | bsz512-seqlen1K | 370K, 157B, 35Hr | 20.17 | 27.17 | 33.92% |
| 6: Baseline | bsz4K-seqlen1K | 37.5K, 157B, 16Hr | 20.99 | 28.09 | 32.54% |
| 7: CL 10K | bsz4K-seqlen1K | 42.5K, 157B, 16Hr | 20.34 | 27.22 | 33.98% |
| 8: CL 20K | bsz4K-seqlen1K | 47.5K, 157B, 16Hr | 20.25 | 27.13 | 34.54% |
| 9: CL 30K | bsz4K-seqlen1K | 52.5K, 157B, 16Hr | 20.22 | 27.15 | 34.16% |
| 10: CL 40K | bsz4K-seqlen1K | 57.5K, 157B, 16Hr | 20.26 | 27.11 | 33.53% |
| 13: Baseline | bsz512-seqlen2K | 150K, 157B, 32Hr | 20.87 | 28.19 | 32.99% |
| 15: CL 70K | bsz512-seqlen2K | 185K, 157B, 31Hr | 19.82 | 26.04 | 33.46% |
| 17: CL 110K | bsz512-seqlen2K | 205K, 157B, 31Hr | 19.64 | 26.03 | 34.58% |
| 18: CL 150K | bsz512-seqlen2K | 215K, 157B, 32Hr | 19.64 | 25.99 | 33.32% |
| 15: CL 190K | bsz512-seqlen2K | 245K, 157B, 33Hr | 19.64 | 26.09 | 33.09% |