FoundationLayerNorm: Scaling BERT and GPT to 1,000 Layers

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Abstract. The mainstream BERT/GPT model contains only 10 to 20 layers, and there is little literature to discuss the training of deep BERT/GPT. This paper proposes a simple yet effective method to stabilize BERT and GPT training. We successfully scale up BERT and GPT to 1,000 layers, which is an order of magnitude deeper than previous BERT and GPT. The proposed method FoundationLayerNormalization enables efficient training of deep neural networks and is validated at the 1000-layer scale.

Keywords: Pre-trained Language Model · Generative Pre-trained Transformer · Bidirectional Encoder Representation from Transformers

1 Introduction

In recent years, there has been a trend in large Transformer models, with capacities increasing dramatically from millions of parameters to billions, or even trillions. Large models yield state-of-the-art performance on a variety of tasks and demonstrate impressive capabilities in few-shot and zero-shot learning. However, scaling to 1,000 layers for BERT or GPT has rarely been reported. To improve the training stability of the BERT and GPT with 1,000 layers, we introduce a new normalization function (FoundationLayerNorm) at the residual connections with a theoretical justification for model updating via constant constraints. This approach improves the stability of the BERT and GPT, so we are able to scale the model depth to more than 1,000 layers. The proposed method can be a preferred alternative for transformers, not only for extremely deep models, but also for existing large models.

In summary, the contributions of this article are as follows:

– We proposed a Layer Normalization method, which was used to train a BERT [3] model with 1,000 layers, which to the best of our knowledge, is the deepest BERT model.
– We proposed a Layer Normalization method, which was used to train a GPT [8] model with 1,000 layers, which to the best of our knowledge, is the deepest GPT model.

2 Background and Related Work

One of the challenges of deep learning is that the gradients with respect to the weights in a layer are highly dependent on the outputs of neurons in the
previous layer, especially if these outputs vary in a highly correlated way. The Batch normalization [4] method normalizes the summed input of each hidden unit on the training instance. Specifically, for the input in the i-th layer, the batch normalization method resizes the input according to the variance under the data distribution, according to the sum of the data.

Liu et. al [5] showed that the decoder is more unstable than the encoder.

Ba et. al [1] found that one way to reduce training time is to regularize the activity of neurons by computing the normalized mean and variance used to sum the inputs to neurons in a layer from all the summed inputs in a single training situation, also giving each neuron its own adaptive bias and gain, which are applied after normalization and before nonlinearity: layer normalization is very effective for stabilizing hidden state dynamics in recurrent networks.

Nguyen et. al [6] found that the pre-norm residual connection (Pre-LN) improves the stability of the transformer based on the post-norm connection (post-LN). However, the gradient of the front LN at the bottom layer tends to be larger than the top layer [11], resulting in a performance degradation compared to the post LN.

Wang et. al [14] proposed the DeepNorm normalization method, extending the transformer to 1,000 layers, the authors scaled the residual connections before performing layer normalization, only the weights of the feedforward network, and the value projection and output projection of the attention layer were scaled.

3 Deep Layer Normalization

The formulation of DEEPNORM [14] can be written as: \( x_{i+1} = LN(\alpha x_i + G_{i}(x_i, \theta_i)) \) where \( \alpha \) is a constant and \( G \) is a function of the i-th Transformer sublayer (i.e. attention or feedforward network) with parameter \( \theta \). Furthermore, DEEPNORM scales the weights \( \theta \) within the residual branch by \( \beta \). Given a BERT model of N-layer encoder, \( \alpha = (2N)^{1/4} \). Given the transformer of N-layer encoder, M-layer decoder, for Transformer-Encoder \( \alpha = 0.81(N^4M)^{1/16} \) and for Transformer-Decoder \( \alpha = (3N)^{1/4} \).

4 Scaling BERT to 1,000 Layers

We processed 9G data as training data, and filtered out code documents from The Pile English dataset.

4.1 Upscale Layer Normalization

We revise the DEEPNORM by keeping the Layer Normalization but holding the weights \( \theta \) within the residual branch, instead of scaling with \( \beta \) as proposed in DEEPNORM by Wang et. al.

The Upscale Layer Normalization formula can be written as: \( x_{i+1} = LN(\alpha x_i + G_{i}(x_i, \theta_i)) \) where \( \alpha \) is a constant and \( G \) is a function of the i-th BERT sublayer.
(i.e. attention or feedforward network) with parameter \( \theta \). Given a BERT model of \( N \)-layer encoder, \( \alpha = (2^N)^{1/4} \).

We use an Nvidia 3090 GPU to pretrain the BERT model for 100k steps for four days, and the loss is 39.6 and the perplex is 4.85e8.

### 4.2 BERT Model Architecture

We use the original BERT [3] tokenizer for our training, which has a vocabulary of 30522. The network structure and hyper-parameters of the model are as follows in Table-1:

| parameters               | value      |
|--------------------------|------------|
| num-parameters           | 52M        |
| num-layers               | 1,000      |
| hidden-size              | 64         |
| num-attention-heads      | 2          |
| seq-length               | 512        |
| learning rate            | 1e-4       |
| min-learning rate        | 1e-5       |
| lr-decay-style           | linear     |
| lr-warmup-fraction       | 0.01       |
| weight-decay             | 0.01       |
| fp16                     | True       |

Table 1. Hyper-parameters for 1,000 layer BERT model.

### 5 Foundation Layer Normalization

The formulation of Foundation Layer Normalization can be written as: \( x_{i+1} = LN(0.974x_i + G_i(x_i, \theta_i)) \) where 0.974 is a constant parameter from experience and \( G \) is a function of the \( i \)-th GPT sublayer (i.e. attention or feedforward network) with parameter \( \theta \).

We processed 200G data as training data, and filtered out code documents from The Pile English dataset. We use an Nvidia 3090 GPU to pretrain the GPT model for 150k steps for seven days, and the loss is 1.28 and the perplex is 3.6.

We use the original GPT-2 [9] tokenizer for our training, which has a vocabulary of 50257. The GPT Model network structure and hyper-parameters of the model are as follows in Table-2:
| parameters          | value  |
|---------------------|--------|
| num-parameters      | 815.5M |
| num-layers          | 1,000  |
| hidden-size         | 256    |
| num-attention-heads | 1      |
| seq-length          | 1024   |
| optimizer           | Adam   |
| learning rate       | 1e-5   |
| lr-decay-style      | cosine |
| lr-warmup-fraction  | 0.01   |
| weight-decay        | 0      |
| fp32                | True   |

Table 2. Hyperparameters for 1,000 layer GPT model.

6 Experiments

6.1 BERT QQP evaluation

Quora Question Pairs (QQP) is a social QA question task proposed by Wang [12]. QQP belongs to a similarity and paraphrase task. There are 364k in the training set and 391k in the test set. We use an Nvidia-3090 GPU to evaluate the BERT model defined in Table-1, and we evaluated for one epoch with batch size of 16, learning rate of 1e-5. The performance result is shown in Table-3.

| task     | precision | recall | f1-score | accuracy |
|----------|-----------|--------|----------|----------|
| QQP-test | 72%       | 69%    | 70%      | 73%      |

Table 3. QQP evaluation for 1,000 layer BERT model.

6.2 GPT QQP evaluation

We evaluate the GPT on Quora Question Pairs [12], LAMBDA [7], Wino-Grande [10], Hellaswag [15] and PIQA [2]. We use an Nvidia-3090 GPU to evaluate the GPT model defined in Table-2.

LAMBADA is a collection of narrative passages sharing the characteristic that human subjects are able to guess their last word if they are exposed to the whole passage, but not if they only see the last sentence preceding the target word. WinoGrande is a collection of 44k problems, inspired by Winograd Schema Challenge (Levesque, Davis, and Morgenstern 2011), but adjusted to improve the
scale and robustness against the dataset-specific bias. Formulated as a fill-in-a-blank task with binary options, the goal is to choose the right option for a given sentence which requires commonsense reasoning. Hellaswag is a commonsense inference challenge dataset. Physical Interaction: Question Answering (PIQA) is a physical commonsense reasoning and a corresponding benchmark dataset. The performance result is shown in Table-4.

| task           | score   |
|----------------|---------|
| QQP-Acc        | 46.93%  |
| QQP-F1         | 48.37%  |
| LAMBADA-PPL    | 8.37E5  |
| LAMBADA-Acc    | 0.72%   |
| Winogradne-Acc | 50.36%  |
| Hellaswag-Acc  | 25.54%  |
| PIQA-Acc       | 55.17%  |

Table 4. QQP evaluation for 1,000 layer GPT model.

6.3 Discussion

Seen from Table-5, with 1/75 parameter size of GPT-J, the GPT-1k achieved competing performance in PIQA and Winogradne datasets.

| Model       | FLOPs  | LAMBADA  | Winogradne | Hellaswag | PIQA   |
|-------------|--------|----------|------------|-----------|--------|
| GPT-2 1.5B  | -      | 51.21%   | 59.4%      | 50.9%     | 70.8%  |
| GPT-Neo 1.3B| 3.0e21 | 57.2%    | 55.0%      | 48.9%     | 71.1%  |
| GPT-Neo 2.7B| 6.8e21 | 62.2%    | 56.5%      | 55.8%     | 73.0%  |
| GPT-J 6B[13]| 1.5e22 | 69.7%    | 65.3%      | 66.1%     | 76.5%  |
| GPT-1k 815.5M(ours) | 3.72e19 | 0.72% | 50.36% | 25.54% | 55.17% |

Table 5. GPT-1k model performance comparison with accuracy of LAMBADA, Winogradne, Hellaswag and PIQA datasets are compared with baseline models.

7 Conclusion

In this paper, two Layer Normalization methods, named Upscale Layer Normalization and Foundation Layer Normalization, are proposed, and the effectiveness of the methods is verified in the BERT and GPT network structures. The proposed method LayerNorm enables efficient training of deep neural networks and
is validated at the 1000-layer scale. The results indicate that depth is a promising extension direction.

8 Future Work

With the development of hardware and software, we will try more efficient model tricks for the deeper network layers and train models based on BERT and GPT in the future.

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