Greenformer: Factorization Toolkit for Efficient Deep Neural Networks

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Abstract

While the recent advances in deep neural networks (DNN) bring remarkable success, the computational cost also increases considerably. In this paper, we introduce Greenformer, a toolkit to accelerate the computation of neural networks through matrix factorization while maintaining performance. Greenformer can be easily applied with a single line of code to any DNN model. Our experimental results show that Greenformer is effective for a wide range of scenarios. We provide the showcase of Greenformer at https://samuelcahyawijaya.github.io/greenformer-demo/.

Introduction

With the significant computational growth of DNN models (Hernandez and Brown 2020), AI researchers all around the globe have started to promote and adopt the concept of ‘Green AI’ (Schwartz et al. 2020). Many recent works (Strubell, Ganesh, and McCallum 2019; Lacoste et al. 2019; Patterson et al. 2021; Dai et al. 2021; Menghani 2021) address the environmental challenges such as energy usage and carbon emission level of DNN models and develop more efficient deep learning solutions. In response to this problem, we introduce a robust and easy-to-use low-rank matrix factorization toolkit which reduces not only the computational cost but also the model size, with minimal performance loss.

Low-rank matrix factorization is done by decomposing a large matrix into two or more smaller matrices, reducing computation and memory costs. Post-training factorization methods with singular-value decomposition (SVD) (Golub and Reinsch 1970) and non-negative matrix factorization (NMF) (Lee and Seung 2001) have been applied to approximate the weight matrix of a trained model (Winata et al. 2019; Ben Noach and Goldberg 2020). On the other line of work, factorization-by-design applies matrix factorization is directly to the model structure prior to the training. This method produces impressive results with the compressed model is not only smaller and faster but also able to outperform the uncompressed model (Winata et al. 2020; Cahyawijaya 2021; Kuchaiev and Ginsburg 2017).

Despite the fact that many works have been published on low-rank matrix factorization, all the solutions are model-dependent, making applicability to different model architecture difficult and cumbersome. To improve the generalization and applicability of the low-rank matrix factorization method, we introduce Greenformer, an eloquent low-rank matrix factorization toolkit that supports multiple use cases of matrix factorization and is currently implemented for the PyTorch framework (Paszke et al. 2019). As shown in Figure 1 with Greenformer, we can easily factorize any deep neural networks to perform both factorization-by-design and post-training factorization. We further demonstrate the effectiveness of our Greenformer toolkit for three different use cases: 1) factorization-by-design, 2) post-training factorization, and 3) few-shot via in-context learning factorization.

Design and Consideration

Greenformer performs decomposition to the weight matrices of linear and convolution layers. Namely, a weight matrix $W \in \mathbb{R}^{m \times n}$ is decomposed into two low-rank matrices $A \in \mathbb{R}^{m \times r}$ and $B \in \mathbb{R}^{r \times n}$, where $r \ll \min\{m, n\}$.

Greenformer decomposes a matrix by utilizing a factor-

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The decomposed matrices and/or tensors are then wrapped into a compatible low-rank module which is then used to replace the original linear an/or convolution layers of the model. Specifically, we replace a linear layer into a Linear Encoder-Decoder (LED) layer and replace a convolution layer into a Convolution Encoder-Decoder (CED) layer. The depiction of LED and/or CED layers work is shown in Figure 3. Both LED, and CED have the same input and output with the linear and convolution layers; hence, they can maintain compatibility with the model.

To maximize the outcome of automatic factorization, Greenformer only performs factorization when the low-rank $r$ is less than the maximum low-rank $r_{\text{max}}$ to ensure reduction of the theoretical computational cost. For a given weight matrix $W \in \mathbb{R}^{m \times n}$ the maximum low-rank is defined as:

$$r_{\text{max}} = \frac{(m \cdot n)}{(m + n)}$$ (1)

To improve its flexibility, Greenformer supports factorization with a dynamic rank across all layers by computing the rank based on a ratio to the maximum rank $r_{\text{max}}$ of the corresponding layer. Additionally, we also observe that applying factorization to all layers of large pretrained models leads to significant performance loss. To address this problem, Greenformer is equipped with a filtering feature that enables factorization only on a specific set of modules.

We test our toolkit on three use cases: 1) Factorization-by-design, where we train models prior to the training; 2) post-training factorization, where we factorize models prior to evaluation phase; and in-context learning factorization, where we apply factorization to large pretrained language models and perform in-context learning following Brown et al. (2020). We test our toolkit on 3 text classification tasks and 2 image classification tasks. We show the effectiveness of our Greenformer toolkit in all use cases in Figure 2.

**Conclusion**

We present Greenformer, an automatic factorization toolkit that provides significant efficiency improvement while maintaining the model performance. In addition, Greenformer is flexible, easy-to-use, and applicable for multiple scenarios. For future work, it is interesting to extend Greenformer for more energy-intensive use cases, such as on large models pretraining and network architecture search.
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