Structured Model Pruning of Convolutional Networks on Tensor Processing Units

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Abstract

The deployment of convolutional neural networks is often hindered by high computational and storage requirements. Structured model pruning is a promising approach to alleviate these requirements. Using the VGG-16 model as an example, we measure the accuracy-efficiency trade-off for various structured model pruning methods and datasets (CIFAR-10 and ImageNet) on Tensor Processing Units (TPUs). To measure the actual performance of models, we develop a structured model pruning library for TensorFlow2 to modify models in place (instead of adding mask layers). We show that structured model pruning can significantly improve model memory usage and speed on TPUs without losing accuracy, especially for small datasets (e.g., CIFAR-10).

1. Introduction

Convolutional neural networks (CNNs) is the dominant approach for many computer vision applications, e.g., image classification (Krizhevsky et al., 2012), object detection (Girshick et al., 2014), and semantic segmentation (Long et al., 2015). The deployment of CNNs in real-world applications, however, is often constrained by model size, memory usage, and computational time. Model pruning is one approach to compress model sizes and accelerate inference (Liu et al., 2015; Han et al., 2016; Wen et al., 2016; Zhou et al., 2016; Li et al., 2017; Scardapane et al., 2017; Anwar et al., 2017; Zhang et al., 2018; Zhu & Gupta, 2018; Deng et al., 2020). Model pruning can be realized at different levels, e.g., weight-level, channel-level, or layer-level. Weight-level (unstructured) pruning has the highest flexibility but usually requires special software or hardware for fast inference (Han et al., 2016). Layer-level structured pruning does not require special packages for inference acceleration but is only effective when the depth is sufficiently large (Wen et al., 2016). Channel-level structured pruning (shown in Fig. 1) balances flexibility and ease of implementation on general accelerators (Liu et al., 2017; Li et al., 2017).

Tensor Processing Units (TPUs) are the dominant approach for deep learning accelerators for Google (Jouppi et al., 2018; 2020). TPUs can be an order faster and more energy-efficient than contemporary GPUs or CPUs (Jouppi et al., 2017). At Google, an auto-tuner for the Accelerated Linear Algebra (XLA) compiler was developed to search for the fastest fusion configurations of an XLA program on TPUs (Kaufman et al., 2020). Unstructured model pruning methods won’t improve efficiency on TPUs because the XLA layout algorithm will pad zeros to the removed individual weights (Kaufman et al., 2020). Whether structured model pruning can lead to efficiency gain on Google TPUs with XLA auto-tuners, however, remains unclear.

In this work, we measure the accuracy-efficiency trade-off for various channel-level structured model pruning methods and datasets on Google TPUs with XLA auto-tuners. Performance (accuracy, memory usage and step time) of pruned models are measured on Google Borg (Verma et al., 2015).

2. Methods

We use a TensorFlow 2 (Abadi et al., 2016) implementation of VGG-16 (Simonyan & Zisserman, 2015) trained on ImageNet (Russakovsky et al., 2015) and CIFAR-10 (Krizhevsky & Hinton, 2009) as an example to study the accuracy-efficiency tradeoff of structured model pruning on TPUs. We train the original model, prune a certain ratio of channels, train the pruned models, and then measure model performance (accuracy, memory usage and step time) during the last epoch of training on Google Borg (Verma et al., 2015).

To find channels to prune, we use scaling factor-based (Liu et al., 2017) and L1 norm-based pruning algorithms (Li et al., 2017). These algorithms estimate the "importance" of a channel based on weights after training, e.g., γ coefficient in the following batch-normalization layer (scaling factor (Liu et al., 2017)) or L1 norm of channel weights (L1 norm (Li et al., 2017)). The least "important" channels will be pruned. We also try whether reloading weights from the
original model helps training of pruned models. To create the pruned models without additional mask layers (so that the actual memory usage and step time can be measured), we create new models with desired structure and then reload corresponding weights from original models if desired.

For all trainings (including original models and pruned models), we use the same hyper-parameters (batch size 128, max epochs 100) and optimizers (SGD (Bottou, 2010) with momentum 0.9 and learning rate 0.01). This is because we aim at the accuracy-efficiency tradeoff of structured model pruning on TPUs rather than the best accuracy.

3. Results

Figure 2 shows accuracy as a function of the pruned ratio of channels on TPUs for CIFAR-10 and ImageNet for various pruning methods. As pruned ratio increases, the accuracy for ImageNet decreases much faster than accuracy for CIFAR-10. To sustain original accuracy, VGG-16 can be pruned by 30% on CIFAR-10 while 10% on ImageNet. At 30% pruned ratio, accuracy for CIFAR-10 is almost the same, while accuracy for ImageNet decreases by 20%, indicating that VGG-16 is over-parameterized for CIFAR-10. CIFAR-10 requires fewer parameters to fit accurately compared with ImageNet because the optimal model size scales with the dataset size (Hestness et al., 2017). VGG-16 is more over-parameterized on CIFAR-10 and a larger pruned ratio can be used without losing accuracy. Accuracy decreases faster and faster when pruned ratio increases (the absolute value of the slope increases) because the first parameters pruned are over-parameterizations. For both datasets, reloading weights from the original model improves pruned accuracy, and scaling factor-based pruning (Liu et al., 2017) leads to better accuracy than L1-norm-based pruning (Li et al., 2017).

Structured model pruning can improve training memory usage (Fig. 3) and step time (Fig. 4) on TPUs. While the saved memory usage, number of pruned parameters, saved step time, and pruned ratio of channels are proportional to each other, they are not strictly linear with each other. This is because the number of parameters of each channel is different, and TPUs will pad zeros to weights according to the XLA layout algorithm (Kaufman et al., 2020).

4. Conclusion

Using the VGG-16 model as an example, we measure the accuracy-efficiency trade-off for various structured model pruning methods and datasets (CIFAR-10 and ImageNet) on TPUs. In both cases, reloading weights from the original model improves pruned accuracy, and scaling factor-based pruning (Liu et al., 2017) leads to better accuracy than L1-norm-based pruning (Li et al., 2017). We show that structured model pruning can significantly improve model memory usage and speed on TPUs without losing accuracy, especially for small datasets (e.g., CIFAR-10). This is because VGG-16 is over-parameterized for a small dataset like CIFAR-10. Our results suggest that structured model pruning is a promising approach to improve the efficiency of CNNs on TPUs.
Figure 2. Accuracy as a function of channel pruned ratio on TPUs for CIFAR-10 and ImageNet for various pruning methods. Black curves use the scaling factor-based pruning algorithm (Liu et al., 2017) and reload weights from original models for training. Red curves use the same pruning algorithm but don’t reload weights from original models. Blue curves use L1 norm-based pruning algorithm (Li et al., 2017) and reload weights from original models.

Figure 3. Memory usage and number of parameters as a function of channel pruned ratio on TPUs for CIFAR-10 and ImageNet.
Figure 4. Training step time as a function of channel pruned ratio on TPUs for CIFAR-10 and ImageNet.
References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., Wicke, M., Yu, Y., and Zheng, X. TensorFlow: A system for large-scale machine learning. In Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2016, pp. 265–283, 2016. ISBN 97819391971331. URL https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi.

Anwar, S., Hwang, K., and Sung, W. Structured pruning of deep convolutional neural networks. ACM Journal on Emerging Technologies in Computing Systems, 13(3), feb 2017. ISSN 15504840. doi: 10.1145/3005348.

Bottou, L. Large-scale machine learning with stochastic gradient descent. In Proceedings of COMPSTAT 2010 - 19th International Conference on Computational Statistics, Keynote, Invited and Contributed Papers, pp. 177–186. Springer Science and Business Media Deutschland GmbH, 2010. ISBN 9783790826036. doi: 10.1007/978-3-7908-2604-3_16. URL https://link.springer.com/chapter/10.1007/978-3-7908-2604-3_16.

Deng, B. L., Li, G., Han, S., Shi, L., and Xie, Y. Model Compression and Hardware Acceleration for Neural Networks: A Comprehensive Survey, apr 2020. ISSN 15582256.

Girshick, R., Donahue, J., Darrell, T., and Malik, J. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 580–587. IEEE Computer Society, sep 2014. ISBN 9781479951178. doi: 10.1109/CVPR.2014.81. URL http://www.cs.berkeley.edu/~rbg/rcnn.

Han, S., Mao, H., and Dally, W. J. Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding. In 4th International Conference on Learning Representations, ICLR 2016 - Conference Track Proceedings. International Conference on Learning Representations, ICLR, oct 2016. URL https://arxiv.org/abs/1510.00149v5.

Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., Patwary, M. M. A., Yang, Y., and Zhou, Y. Deep Learning Scaling is Predictable, Empirically. 2017. URL http://arxiv.org/abs/1712.00409.

Jouppi, N., Young, C., Patil, N., and Patterson, D. Motivation for and Evaluation of the First Tensor Processing Unit. IEEE Micro, 38(3):10–19, may 2018. ISSN 02721732. doi: 10.1109/MM.2018.032271057.

Jouppi, N. P., Young, C., Patil, N., Patterson, D., Agrawal, G., Bajwa, R., Bates, S., Bhatia, S., Boden, N., and Borchers, A. In-datacenter performance analysis of a tensor processing unit. Proceedings of the 44th annual
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International Symposium on Computer Architecture, pp. 1–12, 2017. URL https://dl.acm.org/doi/abs/10.1145/3079856.3080246.

Jouppi, N. P., Yoon, D. H., Kurian, G., Li, S., Patil, N., Laudon, J., Young, C., and Patterson, D. A domain-specific supercomputer for training deep neural networks. Communications of the ACM, 63(7):67–78, 2020. ISSN 15577317. doi: 10.1145/3360307.

Kaufman, S. J., Allen, P. G., Mangpo, P., Brain, P. G., Burrows, M., and Brain, G. Learned TPU Cost Model for XLA Tensor Programs. In NeurIPS, 2020.

Krizhevsky, A. and Hinton, G. Learning multiple layers of features from tiny images. Technical report, 2009. URL https://www.cs.toronto.edu/~kriz/cifar.html.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. ImageNet classification with deep convolutional neural networks. Advances in neural information processing systems, 25:1097–1105, 2012. ISSN 15577317. doi: 10.1145/3065386. URL http://code.google.com/p/cuda-convnet/.

Li, H., Samet, H., Kadav, A., Durdanovic, I., and Graf, H. P. Pruning filters for efficient convnets. In 5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings, aug 2017. URL http://arxiv.org/abs/1608.08710.

Liu, B., Wang, M., Foroosh, H., Tappen, M., and Penksy, M. Sparse Convolutional Neural Networks. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, volume 07-12-June, pp. 806–814, 2015. ISBN 9781467369640. doi: 10.1109/CVPR.2015.7298681.

Liu, Z., Li, J., Shen, Z., Huang, G., Yan, S., and Zhang, C. Learning Efficient Convolutional Networks through Network Slimming. In Proceedings of the IEEE International Conference on Computer Vision, volume 2017-Octob, pp. 2755–2763, 2017. ISBN 9781538610329. doi: 10.1109/ICCV.2017.298.

Long, J., Shelhamer, E., and Darrell, T. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, volume 07-12-June, pp. 431–440. IEEE Computer Society, oct 2015. ISBN 9781467369640. doi: 10.1109/CVPR.2015.729865.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C., and Fei-Fei, L. ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision, 115(3):211–252, dec 2015. ISSN 15731405. doi: 10.1007/s11263-015-0816-y. URL http://image-net.org/challenges/LSVRC/.

Scardapane, S., Comminiello, D., Hussain, A., and Uncini, A. Group sparse regularization for deep neural networks. Neurocomputing, 241:81–89, jul 2017. ISSN 18728286. doi: 10.1016/j.neucom.2017.02.029. URL http://arxiv.org/abs/1607.00485http://dx.doi.org/10.1016/j.neucom.2017.02.029.

Simonyan, K. and Zisserman, A. Very deep convolutional networks for large-scale image recognition. In 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings. International Conference on Learning Representations, ICLR, sep 2015. URL http://www.robots.ox.ac.uk/.

Verma, A., Pedrosa, L., Korupolu, M., Oppenheimer, D., Tune, E., and Wilkes, J. Large-scale cluster management at Google with Borg. In Proceedings of the 10th European Conference on Computer Systems, EuroSys 2015, New York, NY, USA, 2015. ACM. ISBN 9781450332385. doi: 10.1145/2741948.2741964. URL http://dx.doi.org/10.1145/2741948.2741964.

Zhou, H., Alvarez, J. M., and Porikli, F. Less is more: Towards compact CNNs. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), volume 9908 LNCS, pp. 662–677. Springer Verlag, 2016. ISBN 9783319464923. doi: 10.1007/978-3-319-46493-0_40. URL https://link.springer.com/chapter/10.1007/978-3-319-46493-0_40.

Zhu, M. H. and Gupta, S. To prune, or not to prune: Exploring the efficacy of pruning for model compression. In 6th International Conference on Learning Representations, ICLR 2018 - Workshop Track Proceedings, 2018.