26ms Inference Time for ResNet-50: Towards Real-Time Execution of all DNNs on Smartphone

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Abstract

With the rapid emergence of a spectrum of high-end mobile devices, many applications that required desktop-level computation capability formerly can now run on these devices without any problem. However, without a careful optimization, executing Deep Neural Networks (a key building block of the real-time video stream processing that is the foundation of many popular applications) is still challenging, specifically, if an extremely low latency or high accuracy inference is needed. This work presents CADNN, a programming framework to efficiently execute DNN on mobile devices with the help of advanced model compression (sparsity) and a set of thorough architecture-aware optimization. The evaluation result demonstrates that CADNN outperforms all the state-of-the-art dense DNN execution frameworks like TensorFlow Lite and TVM.

1. Introduction

Nowadays, car autopilot and augmented reality (AR) techniques 1 become increasingly popular, which is mainly boosted by the dramatic enhancement of real-time continuous video stream processing in the past few years (Chen et al., 2015). Deep Neural Networks (DNN) such as Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) serve as the state-of-the-art foundation of high-quality real-time continuous video stream processing. Due to its high demand for computation power and memory storage, processing video streams with DNN in real time on modern mobile devices is highly challenging.

There have been many efforts targeting this issue, such as DeepMon (Huynh et al., 2017), DeepX (Lane et al., 2016), DeepSense (Yao et al., 2017), MCDNN (Han et al., 2016), TVM (Chen et al., 2018), TensorFlow Lite (Lite, 2017), etc.; however, most of them do not explore the possible optimization opportunities like computation and memory footprint reductions offered by model compression, including weight pruning (Han et al., 2015; Wen et al., 2016; Zhang et al., 2018a) and weight quantization (Zhou et al., 2017; Wu et al., 2016; Hubara et al., 2016; Rastegari et al., 2016). Therefore, a significant performance gap still exists between the peak performance that can be potentially offered by state-of-art mobile devices and what the existing systems actually achieved.

There are two major obstacles when leveraging model compression to improve the DNN inference execution performance in the mobile environment: first, model compression (like weight pruning/sparsity and weight quantization) usually results in accuracy degradation in inference; and second, the computation pattern of compressed models becomes more irregular, causing more severe data locality and load balancing issues and significantly increasing the difficulty in optimizations.

Within this context, this work proposes CADNN, a programming framework to efficiently execute DNN on mobile devices with a more advanced model compression method that is designed to minimize the accuracy drop and maximize the model compression rate, and a set of careful architecture-aware optimizations that can effectively address the extra irregularity brought by the model compression. To our best knowledge, CADNN offers the most thorough study of optimizing compressed DNN on mobile devices and achieves the most significant performance gains compared to existing state-of-the-art dense DNN execution frameworks.

The contribution of this work is as follows:

• CADNN adopts the advanced model compression method that currently achieves the highest weight pruning rates. It can result in $348 \times$, $36 \times$, and $8 \times$ weight pruning rates with (almost) zero accuracy loss.
two subproblems that can be solved separately and efficiently (Boyd et al., 2011). Consider optimization problem \( \min_x f(x) + g(x) \). In ADMM, it is decomposed into two subproblems on \( x \) and \( z \) (auxiliary variable), which will be solved iteratively until convergence. The first subproblem derives \( x \) given \( z \): \( \min_x f(x) + q_1(x|z) \). The second subproblem derives \( z \) given \( x \): \( \min_z g(z) + q_2(z|x) \). Both \( q_1 \) and \( q_2 \) are quadratic functions.

As a special property, ADMM can effectively deal with a subset of combinatorial constraints and yield optimal (or at least high quality) solutions (Hong et al., 2016). The associated constraints in DNN weight pruning belong to this subset of combinatorial constraints, making ADMM applicable to this specific problem. In weight pruning problem, \( f(x) \) is the DNN loss function and the first subproblem is DNN training with dynamic regularization, which is totally compatible with current gradient descent techniques and solution tools for DNN training. \( g(x) \) corresponds to the combinatorial constraints on the number of weights for weight pruning. As a result of the compatibility with ADMM, the second subproblem has an optimal, analytical solution via Euclidean projection.

The ADMM-based method achieves state-of-art weight pruning results, e.g., \( 21 \times \) overall weight reduction in AlexNet. However, it lacks the algorithm-wise guarantee of solution feasibility, i.e., all constraints should be satisfied. We propose to extend over (Zhang et al., 2018a) in the following three aspects. First, we propose an integration of ADMM regularization and masked mapping and retraining. The former step resembles (Zhang et al., 2018a) while the later step guarantees solution feasibility and further improves solution quality (in terms of pruning rates). Second, we propose a unified solution framework of weight pruning and weight quantization using ADMM. For weight quantization, the combinatorial constraints are also compatible with ADMM. \( g(x) \) corresponds to the combinatorial constraints on the values each weight could take, and the second subproblem again has an optimal analytical solution. Third, we also develop effective techniques, including multi-\( \rho \) technique and progressive model compression, for enhancing convergence speed and quality. We release codes and models at the anonymous link: \url{http://bit.ly/2WmQSRi}.

Our proposed framework achieves the best-in-class weight pruning rate, as well as for weight pruning combined with quantization. For non-structured weight pruning alone, we achieve \( 348 \times \) overall weight reduction (only 0.28% remaining weights) in LeNet-5, \( 36 \times \) in AlexNet (ImageNet dataset), \( 34 \times \) for VGGNet, and \( 9.2 \times \) on ResNet-50, with (almost) no accuracy loss, \( 2 \times \) to 28 \( \times \) improvement over competing methods. We achieve a reduction of up to \( 3,438 \times \) in weight storage (using LeNet-5 model, not accounting for indices), with almost no accuracy loss when weight pruning.
and quantization are combined, outperforming the state-of-art by two orders of magnitude.

4. Architecture-aware Optimization

CADNN supports three major optimizations targeting modern mobile architectures as follows:

**Model computation fusion and transformation** After weight pruning, each layer’s computation is significantly reduced; however, their memory access becomes much more irregular. This further magnifies the memory wall issue of mobile devices, rendering the execution increasingly memory-bound. CADNN therefore explores every opportunity in DNN to fuse multiple layers into larger computation kernels (e.g., Convolution layer/Depthwise Convolution layer + BatchNorm layer + Activation layer in MobileNetV1), yielding benefits in two aspects: first, reducing the intermediate irregular memory read and write therefore improving memory performance; and second, packing more computation workloads together therefore increasing the SIMD (Single-Instruction Multiple Data) utilization. In particular, for convolution layers with $1 \times 1$ filters, CADNN is able to further transform the convolution operation into matrix multiplication operation to further improve its memory and SIMD performance.

**Memory layout transformation and load optimization** To further improve the data locality, CADNN also transforms the memory layout of DNN’s filters to fit CPU and GPU, respectively. More specific techniques include tiling, alignment, and padding. Specifically, based on a key observation that many elements in filters of convolution layers are repeatedly loaded to registers, CADNN implements a compiler code transformation to eliminate such redundant memory loads.

**Optimization parameters selection** Above optimizations work for varied DNNs on both CPU and GPU, however, with very different parameters, e.g., for a specific DNN, the best tile sizes for CPU and GPU are different from each other, and the best tile sizes for varied layers are also different. A large number of optimization parameters (such as tiling sizes on multiple dimensions, unrolling sizes, possible computation reorderings, etc.) imposes a big challenge for us to select the best configuration. CADNN adopts an optimized tuning approach by pruning the redundant or sub-optimal configurations with the knowledge from both DNNs and architectures, and then uses a compiler source-to-source code transformation to generate optimized computation kernels.

5. Evaluation

We compare CADNN’s performance with TensorFlow Lite (a popular framework on the mobile device), and TVM (the state-of-the-art framework).

![Figure 2. Inference performance comparison on CPU/GPU: CADNN-DC (CADNN dense on CPU), CADNN-DG (CADNN dense on GPU), CADNN-SC (CADNN compressed on CPU), CADNN-SG (CADNN compressed on GPU), TFLITE-DC (TensorFlow Lite dense on CPU), TVM-DC (TVM dense on CPU), and TVM-DG (TVM dense on GPU)](image)

**Platform** CADNN is evaluated on a Xiaomi 6 cell phone whose detailed configuration is summarized in Table 1.

| SOC         | Snapdragon 835, up to 2.45GHz |
|------------|--------------------------------|
| GPU        | Adreno 540, 710MHz             |
| Memory     | 6GB shared by CPU and other devices |

**DNNs and data-set** Table 2 characterizes the four DNNs used in our evaluation, showing the model name, size, top-1 accuracy, top-5 accuracy, and the number of layers. All tests are performed on the ImageNet data-set.

**Performance** Figure 2 shows the performance comparison between CADNN and TensorFlow Lite/TVM. CADNN supports both dense and compressed models while TensorFlow Lite and TVM support only dense models. We show CADNN and TVM’s performance on both CPU and GPU, and TensorFlow Lite on CPU only. On both CPU and GPU, CADNN outperforms the other two, achieving up to $6.4 \times$ and $6 \times$ speedup over TVM (that is better than TensorFlow Lite) on CPU and GPU, respectively. This result also demonstrates CADNN is super fast, and with relatively large DNNs, Inception-V3 and Resnet50, it can finish inference of a single image within 35 ms and 21 ms, respectively.

6. Conclusion and Work in Progress

This work presents CADNN, a programming framework to efficiently execute DNN inference on mobile devices with the help of a more advanced model compression and a set of architecture-aware optimizations. Our evaluation shows that CADNN is super fast, achieving up to $8.8 \times$ and
Table 2. DNN Configurations

| Model       | Size(M) | Top1 (%) | Top5 (%) | Layer |
|-------------|---------|----------|----------|-------|
| MobileNet-V1| 17.1    | 70.9     | 89.9     | 31    |
| MobileNet-V2| 14.1    | 71.9     | 91.0     | 66    |
| Inception-V3| 95.4    | 78.0     | 93.9     | 126   |
| ResNet50    | 102.4   | 75.2     | 92.2     | 94    |

6.4× speedup over TensorFlow Lite and TVM, two popular and highly optimized dense DNN execution frameworks. We plan to further optimize CADNN in two aspects: a smarter optimization parameters selection scheme based on other Machine Learning techniques, and a DNN profiler on mobile devices to better detect the performance bottleneck of DNN execution.

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