Hierarchical Block Sparse Neural Networks

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Abstract

Sparse deep neural networks (DNNs) are efficient in both memory and compute when compared to dense DNNs. But due to irregularity in computation of sparse DNNs, their efficiencies are much lower than that of dense DNNs on general purpose hardwares. This leads to poor/no performance benefits for sparse DNNs. Performance issue for sparse DNNs can be alleviated by bringing structure to the sparsity and leveraging it for improving runtime efficiency. But such structural constraints often lead to sparse models with suboptimal accuracies. In this work, we jointly address both accuracy and performance of sparse DNNs using our proposed class of neural networks called HBsNN (Hierarchical Block sparse Neural Networks).

1 Introduction

Deep learning is playing a pivotal role in advancing artificial intelligence. Modern day deep neural networks (DNNs) use millions of parameters to perform well on the task at hand. For instance, Convolutional Neural Networks (CNNs) such as Resnet-50 [He et al. (2016)] and Inception-v3 [Szegedy et al. (2016)] use ~25 and ~23.8 million parameters respectively to achieve state of the art accuracies for image classification task. In general, deep learning methods are data savvy and with increase in data, models with more complexity i.e, more number of parameters are required to achieve better accuracies. This results in an increase in both memory footprint, and compute of the model.

In neural networks, each parameter is equally important before the training begins. As the training progresses, importance of these parameters vary. One can prune away least important parameters during or after the training process with minimal/no loss to the model accuracy. Pruning parameters leads to two benefits: 1) Memory footprint of the model is reduced as we need not store pruned parameters. 2) Computational complexity is decreased as we need not do multiplications involved with pruned parameters. Thus models which are both memory and compute efficient can be generated using pruning techniques. Early studies by [Cun et al. (1990); Hassibi et al. (1993)], have shown the efficacy of pruning technique in reducing the model complexity. More recently, pruning techniques were successfully applied on many classes of neural networks: On Convolutional Neural Networks (CNNs), [Han et al. (2015)] was able to generate sparse CNNs by pruning parameters from a pretrained dense CNNs and follow it by finetuning. On recurrent neural networks (RNNs), [Narang et al. (2017a)] was able to generate sparse RNNs by pruning away parameters at regular intervals during the training process. And also, pruning serves as an effective technique for model compression and can be used alongside with other model compression techniques.

Most common way of pruning is fine grained pruning, where pruning is performed at the level of individual element based on it’s magnitude. If K% of the model parameters are pruned, the computational complexity of the model reduces by a factor of 100/(100-K). For example, pruning

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half of the parameters in the model decreases the computational complexity by 2x. Despite the decrease in computational complexity with fine grained pruning, performance benefits are far from ideal on general purpose hardware due to irregularity in sparse computation. Specialized sparse accelerators have to be built \cite{Han2016, Parashar2017} to cash in benefits of reduced computational complexity due to pruning in sparse neural networks.

To deal with performance issues of sparse neural networks on general purpose hardware, researchers have resorted to pruning parameters in a more structured way and leverage the structure for performance. Towards that end, \cite{Narang2017} have explored block sparsity in Recurrent Neural Networks (RNNs) and were able to generate block sparse RNNs with near SOTA accuracies. But for a given sparsity, block sparse models still have lower accuracies than that of sparse models obtained by fine grained pruning. Parameters in a convolution layer are arranged as a 4D tensor. \cite{Mao2017}, have done a comparative study on the effect of pruning convolution parameters at different levels of granularity (0D, 1D, 2D) on the model accuracy. They have also observed that for a given sparsity, the model accuracy decreases with increase in the coarsity of pruning, and the best accuracy is obtained for fine grained (0D) pruning.

The common observation for structured sparsity is that for a given amount of sparsity, the accuracy of the sparse model is inversely proportional to the rigidity of the imposed structure. Ideally we want our sparse models to have both accuracy and performance. In this work, we arrive at such sparse models using our proposed class of sparse neural networks called HBsNN (Hierarchical Block sparse Neural Networks). The main idea is to have multiple hierarchical structural components which caters for both accuracy and performance. In Table 1, we compare HBsNN on three important vectors with other sparsity types.

| Metrics       | Unstructured sparsity | Highly structured sparsity | Hierarchical block sparsity(HBS) |
|---------------|-----------------------|----------------------------|----------------------------------|
| Low Memory foot print | ✓                     | ✓                          | ✓                                |
| Model accuracy | ✓                     | ×                          | ✓                                |
| Performance   | ×                     | ✓                          | ✓                                |

Table 1: Fixing sparsity in Neural Networks.

Contributions

- Proposed a class of sparse neural networks called HBsNN (Hierarchical Block Sparse Neural Networks), which caters for both accuracy and performance.
- Designed a performance model for the compute in HBsNN.

2 HBsNN

2.1 Motivation

Importance of a parameter in a neural network is strongly correlated with it’s magnitude. When we perform highly structured pruning like block sparse, we lose significant number of high magnitude parameters due to the imposed structural constraints. Row 1 in Table 2 shows the percentage of top \{10, 20, 30, 40\}% elements retained after pruning 60% of elements in a block sparse manner using 4x1 block size on Resnet-v2-50 model. One can see that 11% of the top 10% elements are pruned out. It has been found empirically that high magnitude parameters play a significant role in generating sparse models with good model accuracies. One simple way to retain high magnitude weights is to bring fluidity to the sparsity structure. In Table 2, one can see that for a given sparsity of 60%, incorporating two levels of structure leads to improved top-* percentages. Based on this observation, we propose a class of sparse neural networks called Hierarchical Block sparse Neural Networks (HBsNN) which are more fluid and can retain high magnitude parameters. Sparse models obtained by fine grained pruning and block sparsity are a subset of HBsNN.
| block-size/sparsity | top-10 | top-20 | top-30 | top-40 |
|---------------------|-------|-------|-------|-------|
| 4x1/60              | 89.31 | 76.95 | 68.21 | 61.73 |
| 4x1/63,1x1/97       | 100   | 88.28 | 74.41 | 65.51 |
| 4x1/65,1x1/95       | 100   | 95.48 | 78.46 | 67.95 |
| 4x1/70,1x1/90       | 100   | 100   | 88.16 | 73.78 |
| 4x1/80,1x1/80       | 100   | 100   | 100   | 84.29 |

Table 2: HBS configuration vs Retained percentage on ResNet-v2-50 model.

2.2 DESCRIPTION

In HBsNN (Hierarchical Block Sparse Neural Networks), sparse parameter matrix $M$ of a given layer is composed of multiple sparse parameter matrices i.e, $M = M_1 + ... + M_N$, where each $M_i$ is a block sparse matrix with different block dimensions. As it is suboptimal to split the value of a non-zero in $M$ across many matrix levels, a non-zero element in $M$ is contributed by only one $M_i$ i.e,

$$\forall j,k \in N \mathcal{M}_j \star \mathcal{M}_k = 0.$$

Apart from this, matrices have to satisfy hierarchical structure, where dimensions of block in $M_i+1$ should divide dimensions of block in $M_i$ i.e, $\text{Dim}(M_i) \% \text{Dim}(M_{i+1}) = 0$.

In Figure 1, we have a 3 level configuration with block dimensions 4x4, 2x2 and 1x1 respectively.

![Figure 1: Hierarchical block sparse(HBS) configuration with 3 levels[(4x4),(2x2) and (1x1)].](image)

2.3 PRUNING METHODOLOGY

For a given matrix $I$, block dimensions $(bh, bw)$ and sparsity $sp$, block sparsity is generated by dividing the matrix $I$ into a grid, where each grid element is of size $(bh, bw)$. Each grid element is then given a rank using the absolute summation values of that grid block. We then sort these values and prune away $sp$% of blocks to generate a block sparse matrix. In case of hierarchical block sparsity with $N$ levels, block sizes $BS = [(bh_1, bw_1), \ldots, (bh_N, bw_N)]$ and sparsities $SP = sp_1, \ldots, sp_N$ are provided for all the levels. Let $I_k$ and $M_k$ be the input and output matrices at level $k$. In level $k$, we perform a block sparse pruning with block size $(bh_k, bw_k)$ and sparsity $sp_k$ to generate $M_k$. We then generate input to layer $k+1$ by removing elements of $M_k$ from $I_k$ i.e, $I_{k+1} = I_k - M_k$. Figure 1 shows an example of 2 level HBS pruning on 4x4 matrix with BS=[(2,2),(1,1)] and SP=[50,75]. In case of networks where parameters of a layer are arranged in more than two dimensions, the parameter tensor is flattened to a 2D matrix before applying hierarchical pruning. For example, parameters of a convolution layer in CNN is a 4D tensor $F$ with shape $(K,C,R,S)$. We perform HBS pruning on $F_{mat}$, which is obtained by flattening C,R,S dimensions in that order in $F$. Thus row $i$ in $F_{mat}$ is a flattened array of 3D tensor $F[i,:,:]$. ($F_{mat}[i,:] = F[i,:,:]$).

2.4 PERFORMANCE MODEL

In this section, we describe a performance model for evaluating performance of a layer in HBsNN. For a given HBS configuration, and a mini batch size(bs), let $F_{dense}$ and $F_{sparse}$ be the amount of compute for dense and sparse operations respectively. As a layer in HBsNN has multiple levels($L_1, \ldots, L_N$), $F_{sparse} = \sum_{i=1}^{N} F_{sparse}^{L_i}$, where $F_{sparse}^{L_i}$ is the amount of compute in $i^{th}$ level of the layer. Due to irregularity in sparse computation, it is not always possible to realize the ideal speed up i.e, $F_{dense}/F_{sparse}$. The achievable speedup depends primarily on two factors: 1)Amount
we quantify the sub-optimal speedup with an irregular factor function \( irf(sparsity, blockDimensions) \) parameterized by those two factors. By taking these factors into effect, the cost of dense(\( C_{dense} \)), and the cost of sparse neural network(\( C_{sparse} \)) are defined according to equation 1 and 2. Achievable speedup can then be defined as \( \frac{C_{dense}}{C_{sparse}} \).

\[
C_{dense} = F_{dense} \quad (1) \\
C_{sparse} = \sum_{i=1}^{i=N} \frac{F_{sparse}^{L_i}}{irf(Sparsity(L_i), BlockDims(L_i))} \quad (2)
\]

\[
SpeedUp = \frac{C_{dense}}{C_{sparse}} \quad (3)
\]

3 RESULTS

3.1 ResNet-v2-50/Imagenet

We took a pretrained Renset-v2-50 model with top-1 and top-5 accuracy of 76.13% and 92.86% respectively and then generated sparse models from it using prune and retrain methodology from \cite{Han2015}. In this experiment, we prune all the convolution layers (except first layer) by 60% sparsity with different hierarchical block sparse configurations as shown in Table 3. The pruned model is then trained for 18 epochs with the same set of hyper parameters as that of the pretrained model. The initial learning rate for training is set to \( \frac{1}{100} \)th of the base learning rate used for pretrained model. A step based learning rate decay is followed, where learning rate is decreased by a factor of 10 and 100 respectively at \( 9^{th} \) and \( 14^{th} \) epoch respectively.

| Level-1 (Block-size / sparsity) | Level-2 (Block-size / sparsity) | Top-1 Accuracy | Top-5 Accuracy |
|---------------------------------|---------------------------------|----------------|----------------|
| 4x1/60                          | -                               | 74.81 (-1.32)  | 92.26 (-0.60)   |
| 4x1/63                          | 1x1/97                          | 75.29 (-0.84)  | 92.57 (-0.29)   |
| 4x1/65                          | 1x1/95                          | 75.38 (-0.75)  | 92.57 (-0.29)   |
| 4x1/70                          | 1x1/90                          | 75.48 (-0.65)  | 92.66 (-0.20)   |
| 4x1/80                          | 1x1/80                          | 75.53 (-0.60)  | 92.77 (-0.09)   |
| -                               | 1x1/60                          | 75.76 (-0.37)  | 92.85 (-0.01)   |

Table 3: Two level Hierarchical block sparsity on ResNet-v2-50 model. (Cumulative-Sparsity=60, Block-sizes=[(4x1),(1x1)])

From Table 3 we can see that for the same sparsity level, the accuracy gap can be narrowed down by having fluidity in the structure imposed on sparsity. Just by adding another level, the accuracy for (4x1-63,1x1-97) configuration increases significantly when compared to (4x1/60). This is due to the fact that the former configuration retains high magnitude parameters which are pruned out

\[
\begin{align*}
\text{Figure 2: 2-Level block sparse generation : Block sizes=}(2x2),(1x1)\text{] sparsities=}[50,75] \\
\end{align*}
\]
due to the rigid structural constraint imposed by 4x1 block pruning. Essentially in HBsNN models, levels with smaller block sizes cater for bridging accuracy gap and levels with larger block sizes cater for improving performance. In this particular case, 1x1 caters for accuracy and 4x1 caters for performance. Thus HBsNN models have better accuracies than highly structured sparse models and have better performance than unstructured sparse models. This fluidity in structure is essential for designing better sparse models which are both accurate and performant.

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