Training Larger Models on TensorFlow without Additional GPU

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ABSTRACT

Across different applications, we have seen examples that models with larger capacity achieve better performance. However, the model capacity is ultimately restricted by the limited and expensive GPU memory. In this paper, we present a number of techniques that leverage cheap host memory to reduce GPU memory consumption during training in TensorFlow. Our techniques require no modifications to TensorFlow application programs and enable training models with 3.8× more (up to 2.5 Billion parameters) parameters on a single GPU.

1 INTRODUCTION

Over recent years, deep learning has achieved wide success in many application domains, such as image classification \cite{1}, object detection \cite{2}, machine translation \cite{9} and speech recognition \cite{5}. Over many different applications, it is observed that within the same model class, models with larger capacity (more parameters) achieve better performance. We present some examples found in recent deep learning literature in Table 1.

Due to the computational overhead of deep neural network training, researchers and practitioners often resort to hardware accelerators, such as GPUs for fast training. However, the model size is restricted by the limited and highly expensive GPU memory. GPUs that are most commonly used for deep learning training today are limited to 12 or 16 GB of memory. Fig. 1 compares DRAM price with the price of a number of desktop and server GPUs that are popularly used for neural network training, in terms of $ per MB of on-board memory. We observe that GPU price is not affected by the decreasing DRAM price and remains highly expensive.

Motivated by these challenges, in this paper, we present a mechanism to reduce GPU memory consumption to enable training bigger models by leveraging the cheaper host memory. We implemented those techniques in TensorFlow, without requiring additional input or modifications to the application program \textsuperscript{1}.

\textsuperscript{1}Currently our techniques don’t support computation graphs that use dynamic control flow operators, though this extension should not require significant innovation

2 IMPLEMENTATION AND EVALUATION

2.1 Techniques and Implementation

Partitioned graph execution. TensorFlowMem implements a graph partitioning optimization pass. The graph partitioning pass performs a depth-first traversal of each device’s computation graph and assigns nodes to fixed-size partitions according to the traversal order. Depth-first traversal makes best effort to consume intermediate results as soon as they are produced, instead of holding them in memory for longer durations.

Memory swapping. A graph partition may generate intermediate results that are consumed by partitions that are many sequential steps away in the computation schedule. TensorFlowMem temporarily offloads the intermediate result tensors

Figure 1: Comparing DRAM and GPU price (as dollars per MB of on-board memory).
to host memory and prefetches them by adding SwapOut and SwapIn nodes. Sequential execution across partitions makes it easy to determine when operations are executed and place SwapOut nodes in proper partitions and prefetch CPU tensors shortly before they are needed.

**Operation placement.** A computation graph may contain Variable and Constant nodes that are stateful operations. These nodes are typically packaged with computation operations that use them as an integral building block by higher level programming interfaces, such as Keras [3]. When the application program places the computation operation on GPUs, Variables and Constants are implicitly placed on GPUs as well due to limited programming flexibility. Constant folding folds a subgraph into a Constant operation. The generated Constant operation are placed on the same computing device as the computation operations. TensorFlowMem places Variable and Constant nodes on CPU and loads their value to GPU when needed.

<table>
<thead>
<tr>
<th>System</th>
<th>#Experts</th>
<th>#Param.</th>
<th>Throughput</th>
</tr>
</thead>
<tbody>
<tr>
<td>TensorFlow</td>
<td>12 / MoE</td>
<td>0.66 B</td>
<td>7.8 pairs / sec</td>
</tr>
<tr>
<td>TensorFlowMem</td>
<td>48 / MoE</td>
<td>2.5 B</td>
<td>1.2 pairs / sec</td>
</tr>
</tbody>
</table>

Table 3: Maximum number of experts that can be trained on a single TitanX GPU. We use a batch size of 8 and graph partition size of 200 operations.

**Mixture of Experts.** We evaluate TensorFlowMem using Transformer w/MoE. Table 3 shows the maximum number of experts per MoE layer which can trained using TensorFlow, and TensorFlowMem. TensorFlowMem is able to train 48 experts for MoE layer, which is 4× as many as vanilla TensorFlow. We also find that the throughput decreases roughly linearly with respect to the number of experts when scaling up the MoE layers using TensorFlowMem.

<table>
<thead>
<tr>
<th>Sequence Length</th>
<th>TensorFlow</th>
<th>TensorFlowMem</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.15</td>
<td>1.56</td>
</tr>
<tr>
<td>200</td>
<td>2.3</td>
<td>3.03</td>
</tr>
<tr>
<td>400</td>
<td>4.64</td>
<td>6.03</td>
</tr>
<tr>
<td>500</td>
<td>OOM</td>
<td>-</td>
</tr>
<tr>
<td>800</td>
<td>OOM</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 4: Training iteration time vs. input sequence length

**Longer Recurrence Sequences** For RNNs, the sequence length is often limited by GPU memory size. TensorFlowMem

2We ran TensorFlow both with and without the Grappler memory swapping pass, but obtained the same result both times.
enables training RNNs on longer sequences with a small runtime overhead, which we demonstrate using Mozilla DeepSpeech, a statically unrolled RNN. Our experiments use a mini-batch size of 128 sentences and the partition size of TensorFlowMem is set to 5. Table 4 shows that TensorFlowMem can train DeepSpeech on sequences of length 800 while TensorFlow fails beyond sequence length of 400. Similar to ResNet, TensorFlowMem fails to scale to longer sequences due to the limited host memory. On the same sequence length, TensorFlowMem shows a runtime overhead of roughly 35%.

REFERENCES