COMPRESSING GRADIENT OPTIMIZERS VIA COUNT-SKETCHES

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Rice University, Amazon Search
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Deep Learning is Resource Intensive

Training deep learning models requires large amounts of time and resources
Data-Parallelism for faster training!

A key tool for reducing training time is to increase the batch size.
Data Parallelism – Memory Limitations

Increasing the batch size requires significant amounts of memory
Faster Training vs. Expressive Model

Sacrifice batch size for a larger, more expressive model
Pesky Popular Optimizers

• The auxiliary parameters used by popular optimizers aggravate the memory issue
• i.e. Adam, RMSProp, Adagrad, Momentum
Optimizers – A Concrete Example

• Training BERT Transformer on Nvidia V100 16GB*
• SGD: 10,800 MB, Adam: 13,362 MB
• Auxiliary variables require **2,562 MB extra memory**!

*Using Activation Checkpointing and Mixed Precision Training
Our Goal

• Compress the auxiliary variables
• Maintain convergence rate and accuracy of the full-sized optimizer
Count-Sketches to the Rescue!

- **Solution:** Compress the auxiliary variables with count-sketches
- **Intuition:** Map multiple model parameters to the same parameter in the count-sketch
- **Outcome:** Free memory for more expressive model and/or larger batch size
Highlighted Result - LSTM – LM1B

<table>
<thead>
<tr>
<th>Metric</th>
<th>Adam</th>
<th>Count-Sketch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (Hrs)</td>
<td>5.28</td>
<td>5.42</td>
</tr>
<tr>
<td>Size (MB)</td>
<td>10,813</td>
<td>7,693</td>
</tr>
<tr>
<td>Test Perplexity</td>
<td>39.90</td>
<td>40.55</td>
</tr>
</tbody>
</table>

- Count-Sketch optimizer used 5x fewer parameters
- **Upshot**: Reduced memory usage with minimal accuracy or performance loss
Please visit the poster today!

6:30pm @ Pacific Ballroom #83

GitHub: https://github.com/rdspring1/Count-Sketch-Optimizers