Device Placement Optimization with Reinforcement Learning

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Device Placement

Computation graph

Placement
Placement Challenges

- Heterogeneous clusters (may have mix of CPU/GPUs)
- Traditionally done by a human expert or algorithmic methods (graph partitioning)
  - Unfeasible for complex computation graphs
- Can’t use regular deep learning as our reward (runtime) is non-differentiable -> need to use Reinforcement Learning (RL)
- The placement of a node should take into account the placement of its neighborhood
  - Requires some type of state or ‘memory’ as we place each operation

```
A → B
A or B?
```

A

B

A
The proposed solution:

Use a sequence-to-sequence model as a RL policy network to place operations to devices
Sequence-to-sequence

- Ex: translate a sentence in Spanish to a sentence in English.

- May not be a one-to-one mapping (English sentence may be shorter or longer than the Spanish one).

- Typically structured with two RNNs:
  - “Encoder” network takes our Spanish sentence and converts it to a latent representation.
  - “Decoder” network takes the latent representation and converts it to English.
Sequence-to-sequence in our domain

**Encoder RNN**
- Maps operators to latent space:
  - Type (MatMul, conv2d) +
  - Size of operation's output tensors +
  - Adjacency information

**Decoder LSTM**
- Fixed number of timesteps equal to the number of nodes
- At each step, output the device for the operator corresponding to that timestep
- This assignment is then fed as input to the next decoder timestep
Recurrent Neural Networks & LSTMs

• RNNs maintain internal state, allowing information from past inputs to stay present over time
  • Does so by having cycles which feed activations from prior time step as inputs to the network
  • Often used for sequence data: NLP, speech recognition, financial trading, etc.

• **Problem:** RNNs fail to learn when there are large gaps between the relevant input event and target signal (e.g. more than 10)
  • Vanishing/exploding gradient as inputs cycle through the network’s recurrent connections

LSTMs handle this!
Policy Network

- Uses REINFORCE policy gradient algorithm to minimize running time (our reward signal)
- Running time = one forward pass + one backward pass + one parameter update
Co-location heuristics

• Problem: Tensorflow graphs can have tens of thousands of nodes
  • Would take too long to run all of them through LSTM
• Solution: group operators via heuristics
  • If operation A is only used by operation B, they are co-located
  • All operations in an LSTM “step” are co-located
• This shrinks problem space: no longer finding placement for ALL nodes; we only have to solve placement for each group
• Required to make training time reasonable

<table>
<thead>
<tr>
<th>Model</th>
<th>#operations</th>
<th>#groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNNLM</td>
<td>8943</td>
<td>188</td>
</tr>
<tr>
<td>NMT</td>
<td>22097</td>
<td>280</td>
</tr>
<tr>
<td>Inception-V3</td>
<td>31180</td>
<td>83</td>
</tr>
</tbody>
</table>

Table 1. Model statistics.
Benchmarks

**RNNLM**  
Recurrent Neural Network Language Model

Many LSTM cells in a ‘grid’ structure, where each is only dependent on two of its neighbors. Therefore highly parallelizable

**NMT**  
Neural Machine Translation with attention mechanism

Similar to RNNLM, but more hidden states, so much more computationally expensive

**Inception-V3**  
Image recognition and visual feature extraction

Convolutional network. Lots of parallelization within each “block” of conv + pooling etc., but blocks must be executed sequentially
## Results

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Single-CPU</th>
<th>Single-GPU</th>
<th>#GPUs</th>
<th>Scotch</th>
<th>MinCut</th>
<th>Expert</th>
<th>RL-based</th>
<th>Speedup</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNNLM</td>
<td>6.89</td>
<td><strong>1.57</strong></td>
<td>2</td>
<td>13.43</td>
<td>11.94</td>
<td>3.81</td>
<td><strong>1.57</strong></td>
<td>0.0%</td>
</tr>
<tr>
<td>(batch 64)</td>
<td></td>
<td></td>
<td>4</td>
<td>11.52</td>
<td>10.44</td>
<td>4.46</td>
<td><strong>1.57</strong></td>
<td>0.0%</td>
</tr>
<tr>
<td>NMT</td>
<td>10.72</td>
<td>OOM</td>
<td>2</td>
<td>14.19</td>
<td>11.54</td>
<td>4.99</td>
<td><strong>4.04</strong></td>
<td>23.5%</td>
</tr>
<tr>
<td>(batch 64)</td>
<td></td>
<td></td>
<td>4</td>
<td>11.23</td>
<td>11.78</td>
<td>4.73</td>
<td><strong>3.92</strong></td>
<td>20.6%</td>
</tr>
<tr>
<td>Inception-V3</td>
<td>26.21</td>
<td><strong>4.60</strong></td>
<td>2</td>
<td>25.24</td>
<td>22.88</td>
<td>11.22</td>
<td><strong>4.60</strong></td>
<td>0.0%</td>
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<tr>
<td>(batch 32)</td>
<td></td>
<td></td>
<td>4</td>
<td>23.41</td>
<td>24.52</td>
<td>10.65</td>
<td><strong>3.85</strong></td>
<td>19.0%</td>
</tr>
</tbody>
</table>
Results (cont.)

- RL agent achieves better balance…
Results (cont.)

• But only when it makes sense to!
Problems...

- Network must be re-trained for each computation graph; therefore training time is an important metric. 12 to 27 hours on their benchmarks!

- Co-location heuristics are a “necessary evil” to improve training time. Some graphs would be uncomputable otherwise.

- **Downsides:**
  - Some good placements are made impossible (i.e. an LSTM step cannot be parallelized using their heuristics)
  - The user must configure which heuristics should be used on their computation graph.
    - Back to using human experts!
Follow-up:

A Hierarchical Model for Device Placement

Azalia Mirhoseini, Anna Goldie, Hieu Pham, Benoit Steiner, Quoc V. Le, Jeff Dean
How it works

• Replace the co-location heuristics with a network which learns to assign operations to groups. (The “Grouper”)

• Use the previous LSTM approach as before to find placements for each group. (The “Placer”)

• Why?
  • No more human involvement (co-location is automatically learned)
  • Can handle large graphs (by grouping down until its feasible to solve)
  • Can find placements that co-location heuristics would omit
The Grouper makes co-location decisions independently (simple feed-forward network)

The Placer is conditional based upon prior device assignments (LSTM + attention)
## Results

<table>
<thead>
<tr>
<th>Tasks</th>
<th>CPU Only</th>
<th>GPU Only</th>
<th>#GPUs</th>
<th>Human Expert</th>
<th>Scotch</th>
<th>MinCut</th>
<th>Hierarchical Planner</th>
<th>Runtime Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inception-V3</td>
<td>0.61</td>
<td>0.15</td>
<td>2</td>
<td>0.15</td>
<td>0.93</td>
<td>0.82</td>
<td>0.13</td>
<td>16.3%</td>
</tr>
<tr>
<td>ResNet</td>
<td>-</td>
<td>1.18</td>
<td>2</td>
<td>1.18</td>
<td>6.27</td>
<td>2.92</td>
<td>1.18</td>
<td>0%</td>
</tr>
<tr>
<td>RNNLM</td>
<td>6.89</td>
<td>1.57</td>
<td>2</td>
<td>1.57</td>
<td>5.62</td>
<td>5.21</td>
<td>1.57</td>
<td>0%</td>
</tr>
<tr>
<td>NMT (2-layer)</td>
<td>6.46</td>
<td>OOM</td>
<td>2</td>
<td>2.13</td>
<td>3.21</td>
<td>5.34</td>
<td>0.84</td>
<td>60.6% v. 19.0%</td>
</tr>
<tr>
<td>NMT (4-layer)</td>
<td>10.68</td>
<td>OOM</td>
<td>4</td>
<td>3.64</td>
<td>11.18</td>
<td>11.63</td>
<td>1.69</td>
<td>53.7% v. OOM</td>
</tr>
<tr>
<td>NMT (8-layer)</td>
<td>11.52</td>
<td>OOM</td>
<td>8</td>
<td>3.88</td>
<td>17.85</td>
<td>19.01</td>
<td>4.07</td>
<td>-4.9% v. OOM</td>
</tr>
</tbody>
</table>
In Conclusion

• Training time limitation still present. Hierarchical approach is 3hrs instead of 27hrs, but still not insignificant.

• These are the first two papers to use RL for device placement

• A small set of others works have tried this since, with varying success:
  • REGAL: use RL to tune a genetic algorithm to solve placement
  • Placeto: use a GNN to learn representations, then use RL for placement (no RNNs)
    • Big bonus: generalizable to other graphs! (No more retraining)
      • Still not fully successful…
Questions?