A flexible, extensible software framework for model compression based on the LC algorithm

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The code is available at:
https://github.com/UCMerced-ML/LC-model-compression
The fundamental problem of model compression: what to choose?

- Reference (uncompressed)
- Pruning
- Low-rank

Images are from the slides of Miguel Á. Carreira-Perpiñán
Challenges

In principle, we want to explore all possible combinations, and select the best. But:

- Many compression schemes ⇒ many algorithms
- How to maintain a library of many compressions?
- How to make it user friendly?
  - many algorithms ⇒ many failure points
- How to make it extensible and easily maintainable?

We propose a software based on the Learning-Compression (LC) algorithm:

- single algorithm—many compressions
- extensible, modular, and fast
- impressive compression results
- open source: BSD 3-clause license
The LC algorithm: formulation

Given a network with weights $\mathbf{w}$ and loss $L$:

$$\min_{\mathbf{w}, \Theta} L(\mathbf{w}) \quad \text{s.t.} \quad \mathbf{w} = \Delta(\Theta)$$  \hspace{1cm} (1)

The compression details are abstracted in $\Delta(\Theta)$:

- e.g., low-rank: $\Delta(\Theta) = \mathbf{U}\mathbf{V}^T$ where $\Theta = \{\mathbf{U}, \mathbf{V}\}$

The feasible models $C$ are decompressible by $\Delta$:

$$\mathbf{w}^* \ (\text{optimal compressed})$$

feasible models $C = \{\mathbf{w} \in \mathbb{R}^P : \mathbf{w} = \Delta(\Theta) \text{ for } \Theta \in \mathbb{R}^Q\}$

figure from the slides of Miguel Á. Carreira-Perpiñán
The LC algorithm (cont.)

The problem (1) can be solved by alternation of these two steps (while driving $\mu \to \infty$), which form the basis of our software:

- **Learning (L) step:**
  \[
  \min_w L(w) + \frac{\mu}{2} \| w - \Delta(\Theta) \|^2
  \]

  - This is a regular training of the model, but with a quadratic regularization term
  - When you train a network, you already have the L step.

- **Compression (C) step:**
  \[
  \min_{\Theta} \| w - \Delta(\Theta) \|^2
  \]

  - Independent of the loss, neural network structure, and the dataset.
  - We provide a library of different C steps for many different compressions.
# The library of implemented compressions

<table>
<thead>
<tr>
<th>Type</th>
<th>Forms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quantization</strong></td>
<td>Adaptive Quantization into ( {c_1, c_2, \ldots c_K} )</td>
</tr>
<tr>
<td></td>
<td>Binarization into ( {-1, 1} ) and ( {-c, c} )</td>
</tr>
<tr>
<td></td>
<td>Ternarization into ( {-c, 0, c} )</td>
</tr>
<tr>
<td><strong>Pruning</strong></td>
<td>( \ell_0 )-constraint (s.t., ( |w|_0 \leq \kappa ))</td>
</tr>
<tr>
<td></td>
<td>( \ell_1 )-constraint (s.t., ( |w|_0 \leq \kappa ))</td>
</tr>
<tr>
<td></td>
<td>( \ell_0 )-penalty (( \alpha |w|_0 ))</td>
</tr>
<tr>
<td></td>
<td>( \ell_1 )-penalty (( \alpha |w|_1 ))</td>
</tr>
<tr>
<td><strong>Low-rank</strong></td>
<td>Low-rank compression to a given rank</td>
</tr>
<tr>
<td></td>
<td>Low-rank with <em>automatic</em> rank selection for FLOPs reduction</td>
</tr>
<tr>
<td></td>
<td>Low-rank with <em>automatic</em> rank selection for storage compression</td>
</tr>
<tr>
<td><strong>Additive Combinations</strong></td>
<td>Quantization + Pruning</td>
</tr>
<tr>
<td></td>
<td>Quantization + Low-rank</td>
</tr>
<tr>
<td></td>
<td>Pruning + Low-rank</td>
</tr>
<tr>
<td></td>
<td>Quantization + Pruning + Low-rank</td>
</tr>
</tbody>
</table>
Easy exploration of compressions

Having an L-step implementation (you only need one), definition of compression is very simple:

quantize each layer with separate codebooks

```
compression_tasks = {
    Param(l1.weight): (AsVector, AdaptiveQuantization(k=2)),
    Param(l2.weight): (AsVector, AdaptiveQuantization(k=2)),
    Param(l3.weight): (AsVector, AdaptiveQuantization(k=2))
}
```

prune all but 5%

```
compression_tasks = {
    Param([l1.weight, l2.weight, l3.weights]):
        (AsVector, ConstraintL0Pruning(kappa=13310)) # 13310 = 5%
}
```

prune first layer, low-rank to second, quantize third

```
compression_tasks = {
    Param(l1.weight): (AsVector, ConstraintL0Pruning(kappa=5000)),
    Param(l2.weight): (AsIs, LowRank(target_rank=10))
    Param(l3.weight): (AsVector, AdaptiveQuantization(k=2))
}
```
Our framework achieves competitive results in many compression schemes. For example, using our code for rank-selection, we can achieve considerable speed-up on AlexNet:

<table>
<thead>
<tr>
<th></th>
<th>MFLOPs</th>
<th>top-1</th>
<th>top-5</th>
<th>$\rho_{\text{FLOPs}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caffe-AlexNet [1]</td>
<td>724</td>
<td>42.70</td>
<td>19.80</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>our, scheme 1, $\lambda = 0.17$</strong></td>
<td>240</td>
<td>42.83</td>
<td>19.93</td>
<td>3.01</td>
</tr>
<tr>
<td><strong>our, scheme 2, $\lambda = 0.20$</strong></td>
<td>151</td>
<td><strong>42.69</strong></td>
<td>19.83</td>
<td><strong>4.79</strong></td>
</tr>
<tr>
<td>Kim et al. [2], Tucker</td>
<td>272</td>
<td>n/a</td>
<td>21.67</td>
<td>2.66</td>
</tr>
<tr>
<td>Tai et al. [3], scheme 2</td>
<td>185</td>
<td>n/a</td>
<td>20.34</td>
<td>3.90</td>
</tr>
<tr>
<td>Wen et al. [4], scheme 1</td>
<td>269</td>
<td>n/a</td>
<td>20.14</td>
<td>2.69</td>
</tr>
<tr>
<td>Kim et al. [5], scheme 2</td>
<td>272</td>
<td>43.40</td>
<td>20.10</td>
<td>2.66</td>
</tr>
<tr>
<td>Yu et al. [6], filter prun.</td>
<td>232</td>
<td>44.13</td>
<td>n/a</td>
<td>3.12</td>
</tr>
<tr>
<td>Li et al. [7], filter prun.</td>
<td>334</td>
<td>43.17</td>
<td>n/a</td>
<td>2.16</td>
</tr>
<tr>
<td>Ding et al. [8], filter prun.</td>
<td>492</td>
<td>43.83</td>
<td>20.47</td>
<td>1.47</td>
</tr>
</tbody>
</table>

Compression with our algorithm vs published work using low-rank methods and structured pruning. $\rho_{\text{FLOPs}}$ — reduction in FLOPs.

Example: Additive compressions to achieve smallest AlexNet-s

The codebase allows easy exploration of new compression mechanisms. For example, we can further compress low-rank AlexNet models to target storage:

<table>
<thead>
<tr>
<th>Model</th>
<th>top-1 size, MB</th>
<th>MFLOPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caffe-AlexNet Jia et al. [1]</td>
<td>42.70</td>
<td>243.5</td>
</tr>
<tr>
<td>L₁ → Q (1-bit) + P (0.25M)</td>
<td><strong>41.56</strong></td>
<td>3.7</td>
</tr>
<tr>
<td>L₂ → Q (1-bit) + P (0.25M)</td>
<td>41.91</td>
<td>2.8</td>
</tr>
<tr>
<td>L₃ → Q (1-bit) + P (0.25M)</td>
<td>42.85</td>
<td><strong>2.2</strong></td>
</tr>
<tr>
<td>AlexNet-QNN of Wu et al. [10]</td>
<td>44.24</td>
<td>13.0</td>
</tr>
<tr>
<td>P→₁Q of Han et al. [11]</td>
<td>42.78</td>
<td>6.9</td>
</tr>
<tr>
<td>P→₂Q of Choi et al. [12]</td>
<td>43.80</td>
<td>5.9</td>
</tr>
<tr>
<td>P→₃Q of Tung and Mori [13]</td>
<td>42.10</td>
<td>4.8</td>
</tr>
<tr>
<td>P→₄Q of Yang et al. [14]</td>
<td>42.48</td>
<td>4.7</td>
</tr>
<tr>
<td>P→₅Q of Yang et al. [14]</td>
<td>43.40</td>
<td>3.1</td>
</tr>
<tr>
<td>filter pruning of Li et al. [7]</td>
<td>43.17</td>
<td>232.0</td>
</tr>
</tbody>
</table>

![Storage error vs. top-1 test error](image-url)
Source code and library features

Our code is written in Python using PyTorch, and open source under BSD 3-clause license:

https://github.com/UCMerced-ML/LC-model-compression

Using the provided code, you will be able to:

- replicate all reported experiments
- compress your own models with many available compression schemes

Our library is:

- modular and easily extensible
- only requires the L-step implementation: the regular learning of the model (using SGD)
- based on solid optimization principles
- single algorithm—many compressions
- time proven (development since 2017), with many publications [9, 15, 16, 17, 18]
References


