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

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We propose a software framework based on the ideas of the *Learning-Compression (LC) algorithm* [1–3, 5, 6], that allows a user to compress a neural network or other machine learning model using different compression schemes with minimal effort. Currently, the supported compressions include pruning, quantization, low-rank methods (including automatically learning the layer ranks), and combinations of those, and the user can choose different compression types for different parts of a neural network. The library is written in Python and PyTorch and available online at https://github.com/UCMerced-ML/LC-model-compression

Among the various research strands in neural net compression, in our view, the fundamental problem is that in practice, one does not know what type of compression (or combination of compression types) may be the best for a given network. In principle, it may be possible to try different existing algorithms, assuming one can find an implementation for them, but practically it is often impossible. We seek a solution that directly addresses this problem and allows non-expert end-users to compress models easily and efficiently. Our approach is based on a recently proposed compression framework, the LC algorithm [1–3, 5, 6], that by design separates the "learning" part of the problem, which involves the dataset, neural net model, and loss function from the "compression" part, which defines how the network parameters will be compressed. This separation has advantage of 1) *optimality*, as it is derived by application of solid optimization principles to a well defined problem involving model's loss and compression constraints 2) *modularity*: we can change the compression type by simply calling a different compression routine (e.g., k-means instead of the SVD), with no other changes to the algorithm.

The backbone of our software is the LC algorithm [1] which solves a following model compression problem with weights $\mathbf{w}$, compression constraints $\boldsymbol{\Delta}(\boldsymbol{\Theta})$, and model loss L (e.g., cross-entropy):

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

The algorithm alternates two types of steps until convergence:

- a *learning (L) step* of $\min_{\mathbf{w}} L(\mathbf{w}) + \frac{\mu}{2}\left\|\mathbf{w} - \boldsymbol{\Delta}(\boldsymbol{\Theta})\right\|^2$, which trains a model on a dataset (using an algorithm such as SGD)
- a *compression (C) step* of $\min_{\boldsymbol{\Theta}} \left\|\mathbf{w} - \boldsymbol{\Delta}(\boldsymbol{\Theta})\right\|$, which compresses the model parameters (using a compression scheme such as low-rank or quantization).

This decoupling of the "machine learning" aspect from the "signal compression" aspect means that changing the model or the compression type amounts to calling the corresponding subroutine in the L or C step, respectively. The library fully supports this by design, which makes it flexible and extensible. This does not come at the expense of performance: the runtime needed to compress a model is comparable to that of training the model in the first place; and the compressed model is competitive in terms of prediction accuracy and compression ratio with other algorithms.

To run the model compression, user needs to provide an implementation of the L-step and description of compression task. The list of currently supported compression types is given in Table 1 and can be easily extended by implementing a new C-step. The compressions can by applied on a layer or multi-layer granularity, and multiple compressions can be mixed in the same model. A typical implementation of the L step and boilerplate code to use the library is given in Figure 1.

Type	Forms
Quantization	Adaptive Quantization into $\{c_1, c_2, \dots c_K\}$ Binarization into $\{-1, 1\}$ and $\{-c, c\}$ Ternarization into $\{-c, 0, c\}$
Pruning	ℓ_0-constraint (s.t., $\|\mathbf{w}\|_0 \le \kappa$) ℓ_1-constraint (s.t., $\|\mathbf{w}\|_0 \le \kappa$) ℓ_0-penalty ($\alpha\|\mathbf{w}\|_0$) ℓ_1-penalty ($\alpha\|\mathbf{w}\|_1$)
Low-rank	Low-rank compression to a given rank Low-rank with *automatic* rank selection for FLOPs reduction Low-rank with *automatic* rank selection for storage compression
Additive Combinations	Quantization + Pruning Quantization + Low-rank Pruning + Low-rank Quantization + Pruning + Low-rank

Table 1: Currently supported compression types and C-step implementations, with their exact forms.

```
def my_l_step(model, lc_penalty, args**):
  # ... skipped ...
  loss = model.loss(out_, target_) + lc_penalty()
  loss.backward()
  optimizer.step()
  # ... skipped ...
```

```
lc_alg = lc.Algorithm(
  model=net,  # a model to compress
  compression_tasks=compression_tasks,
  l_step_optimization=my_l_step,
)
lc_alg.run()
```

Figure 1: *Left:* a typical implementation of the L step using PyTorch; some code is skipped for brevity. *Right:* The boilerplate code to run a compression on a given model.

Experimental validation The LC algorithm is efficient in runtime; it does not take much longer than training the reference, uncompressed model in the first place. The compressed models perform very competitively and allow the user to easily explore the space of prediction accuracy of the model vs compression ratio. In Figure 2 we give an example of such exploration for low-rank compression on CIFAR10 models.

Using our code, in [6] we compress the AlexNet model trained on ImageNet with reference top-1 error of 42.70% that has 240MB of weight storage and 724M of FLOPs into a model with 4.3MB of weight storage and 238M of FLOPs while simultaneously improving its top-1 error to 41.54%.

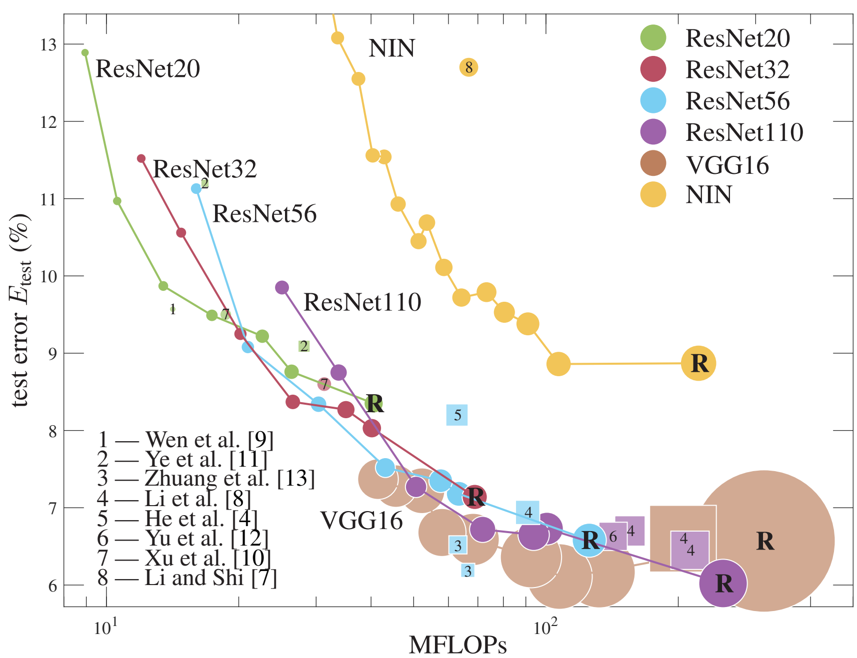

Figure 2: Error-compression space of test error (Y axis), inference FLOPs (X axis) and number of parameters (ball size for each net), on CIFAR10 models (different color for each model family). Results of our algorithm span a curve, shown as connected circles; **R** — reference model.

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