More General and Effective Model Compression via an Additive Combination of Compressions

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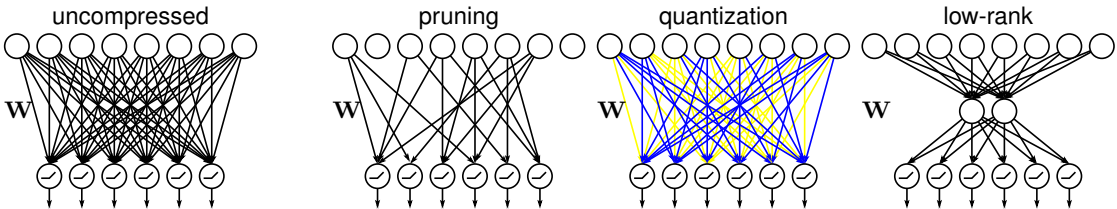
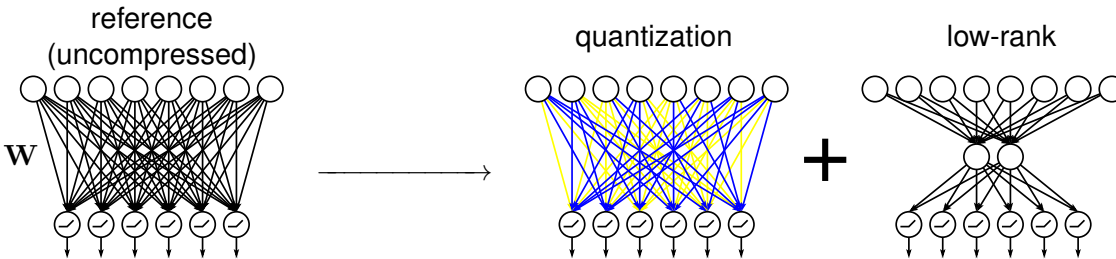
The code is available at:
https://github.com/UCMerced-ML/LC-model-compression

Introduction

Compression of neural networks become an important practical problem with plethora of works and approaches in recent years.



Introduction: Additive Combinations



We replace a matrix $\mathbf{W}$ with an additive combination of compressed matrices (e.g., quantization + low-rank)

- This allows to greatly improve the "power" of the scheme:
  - it is at least as powerful as each of the containing compressions
  - it allows techniques to help each other: i.e., correct where other scheme is failing
- How to make such compression happen for an arbitrary combination?
- We give a suitable formulation and optimization algorithm, followed by its empirical evaluation

Problem formulation

Given a model with weights $\mathbf{w}$ and loss L we formulate the problem of

$$\min_{\mathbf{w},\boldsymbol{\theta}_1,\boldsymbol{\theta}_2} \quad L(\mathbf{w}) \quad \text{s.t.} \quad \mathbf{w} = \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) + \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2). \tag{1}$$

- $\boldsymbol{\Delta}_i$ is a mapping from a low-dimensional (compressed) parameter $\boldsymbol{\theta}_i$ into original weight space
  - Low-rank: $\mathbf{W} = \mathbf{U}\mathbf{V}^T$ with $\mathbf{U}$ and $\mathbf{V}$ of rank r, so $\boldsymbol{\theta} = (\mathbf{U}, \mathbf{V})$.
  - Pruning: $\mathbf{w} = \boldsymbol{\theta}$ s.t. $\|\boldsymbol{\theta}\|_0 \leq \kappa$, so $\boldsymbol{\theta}$ is the indices of its nonzeros and their values.
  - Binarization: $w \in \{-1, +1\}$ or equivalently a scalar quantization with $\mathcal{C} = \{-1, +1\}$.
- Although our approach can handle any number of combinations, for brevity we discuss a combination of two compressions

Optimization algorithm

We apply a penalty method and obtain an equivalent formulation (with $\mu \to \infty$):

$$Q(\mathbf{w}, \boldsymbol{\theta}; \mu) = L(\mathbf{w}) + \frac{\mu}{2} \|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2 \tag{2}$$

Here, we use Quadratic Penalty for the ease of presentation, however, in practice we use augmented Lagrangian with the additional step over Lagrange multipliers

Let us now apply alternating optimization over variables $\mathbf{w}$ and $\{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2\}$:

- The step over $\mathbf{w}$, which we call a learning (L) step, has the form of:

$$\min_{\mathbf{w}} \quad L(\mathbf{w}) + \frac{\mu}{2} \|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$$

  The problem wrt $\mathbf{w}$ is fully differentiable and has a form of loss + ℓ_2 penalty. We use SGD.

- The step over $\{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2\}$, which we call a compression (C) step, has the form of:

$$\min_{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2} \|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$$

  Actual compression step independent of NN weights and dataset.

Optimization algorithm: More on C step

Although our decomposition simplifies model compression into a problem of much smaller dimensions of

$$\min_{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2} \|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$$

Its optimization wrt $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ can still be challenging. Therefore, we apply alternating optimization one more time:

$$\begin{aligned} \boldsymbol{\theta}_1 &= \arg\min_{\boldsymbol{\theta}} \|(\mathbf{w} - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)) - \boldsymbol{\Delta}_1(\boldsymbol{\theta})\|^2 \\ \boldsymbol{\theta}_2 &= \arg\min_{\boldsymbol{\theta}} \|(\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1)) - \boldsymbol{\Delta}_2(\boldsymbol{\theta})\|^2 \end{aligned} \tag{3}$$

These steps now can be computed much easier: for low-rank it requires SVD, for pruning it needs thresholding, etc.

Optimization algorithm (pseudocode)

input training data, neural net architecture with weights $\mathbf{w}$

$\mathbf{w} \leftarrow \arg\min_{\mathbf{w}} L(\mathbf{w})$ — reference net

$\boldsymbol{\theta}_1, \boldsymbol{\theta}_2 \leftarrow \arg\min_{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2} \|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$ — init

for $\mu = \mu_1 < \mu_2 < \cdots < \mu_T$

  $\mathbf{w} \leftarrow \arg\min_{\mathbf{w}} L(\mathbf{w}) + \frac{\mu}{2}\|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$ — L step

  while alternation does not converge

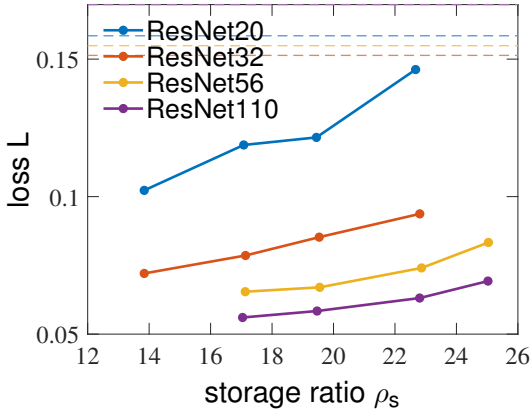
    $\boldsymbol{\theta}_1 \leftarrow \arg\min_{\boldsymbol{\theta}_1} \|(\mathbf{w} - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)) - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1)\|^2$ — C step

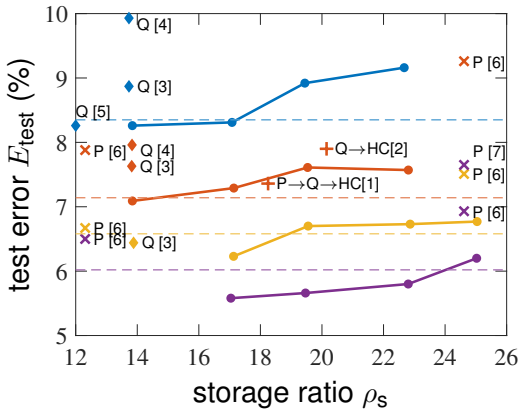
    $\boldsymbol{\theta}_2 \leftarrow \arg\min_{\boldsymbol{\theta}_2} \|(\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1)) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|^2$

  if $\|\mathbf{w} - \boldsymbol{\Delta}_1(\boldsymbol{\theta}_1) - \boldsymbol{\Delta}_2(\boldsymbol{\theta}_2)\|$ is small enough **then** exit the loop

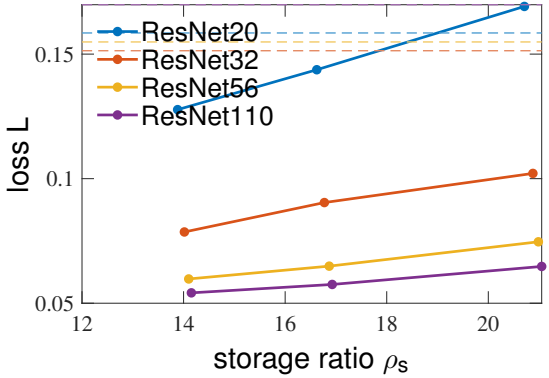
return $\mathbf{w}, \boldsymbol{\theta}_1, \boldsymbol{\theta}_2$

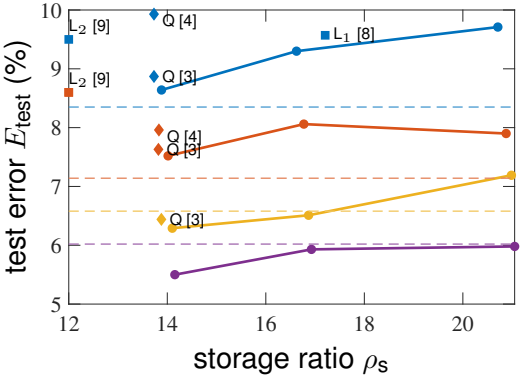
Experiments: Quantization + Pruning on ResNets (CIFAR10)





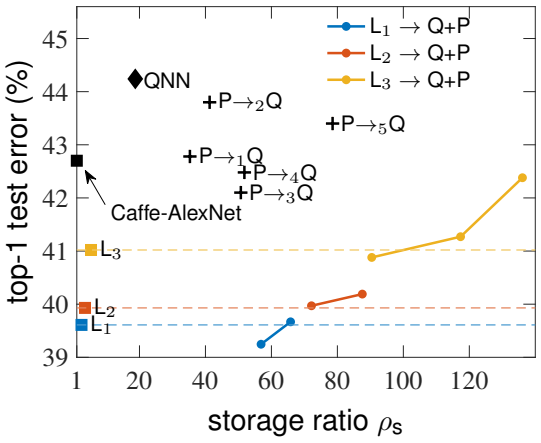
Experiments: Quantization + Low-rank on ResNets (CIFAR10)





Experiments: Q+P on already compressed AlexNets (ImageNet)

	Model	top-1	MBs	MFLOPs
	Caffe-AlexNet [10]	42.70	243.5	724
	R Low-rank AlexNet (L_1)	39.61	100.5	227
ours	$L_1 \rightarrow$ Q + P (0.25M)	39.67	3.7	227
ours	$L_1 \rightarrow$ Q + P (0.50M)	**39.25**	4.3	227
	R Low-rank AlexNet (L_2)	39.93	69.8	185
ours	$L_2 \rightarrow$ Q + P (0.25M)	40.19	2.8	185
ours	$L_2 \rightarrow$ Q + P (0.50M)	39.97	3.4	185
	R Low-rank AlexNet (L_3)	41.02	45.9	**152**
ours	$L_3 \rightarrow$ Q + P (0.125M)	42.38	**1.8**	**152**
ours	$L_3 \rightarrow$ Q + P (0.25M)	41.27	2.1	**152**
ours	$L_3 \rightarrow$ Q + P (0.50M)	40.88	2.7	**152**



Code is available online

Our code is written in `Python` using `PyTorch`, and we make it available as part our extensible model compression framework (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 our proposed scheme and many others.

But this library does much more than that. It is intended to support compression of an arbitrary model (not just neural nets) and an arbitrary compression technique. At the moment it offers the following:

- quantization (in various forms)
- pruning (in various forms)
- low-rank with automatic rank and/or scheme selection
- combinations of all the above

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