Model Compression with Adversarial Robustness: A Unified Optimization Framework

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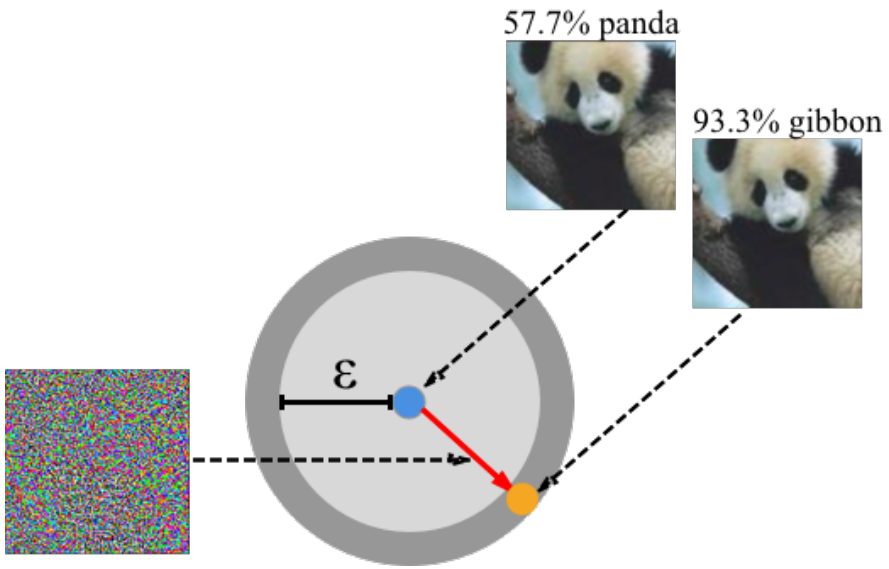
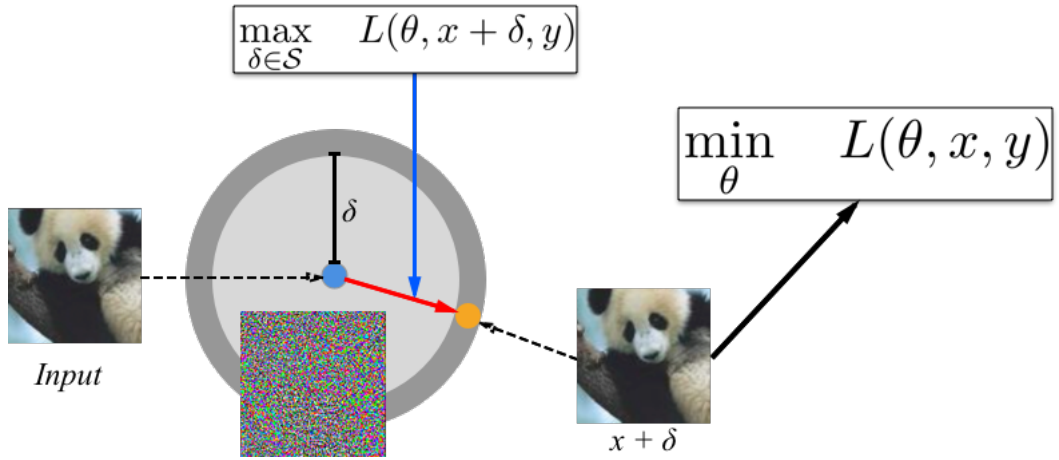
Highlights

- Compressing models without hurting their robustness to adversarial attacks, in addition to maintaining accuracy
- Adversarially Trained Model Compression (ATMC) framework
- Integrating pruning, factorization, and quantization into constraints
- An extensive group of experiments demonstrate that ATMC obtains remarkably more favorable trade-off among model size, accuracy and robustness, over currently available alternatives in various settings.

Robustness for CNN



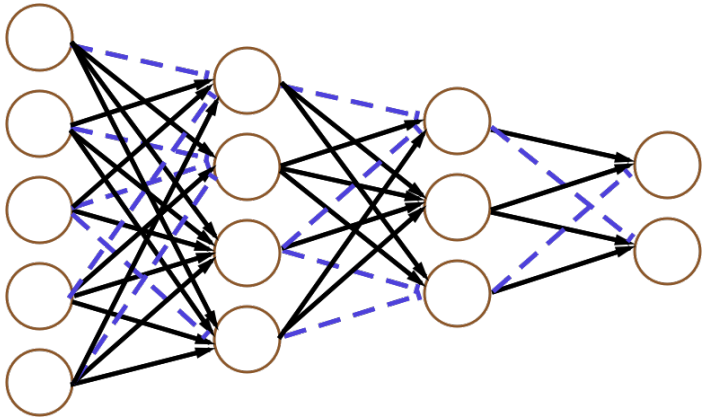


$$\min_{\theta} \rho(\theta), \quad \text{where } \rho(\theta) = \mathbb{E}_{(x,y)\in\mathcal{D}} \left[\max_{\delta} L(\delta, x+\delta, y) \right]$$

Goodfellow et al, "Explaining and Harnessing Adversarial Examples", ICLR 2015.

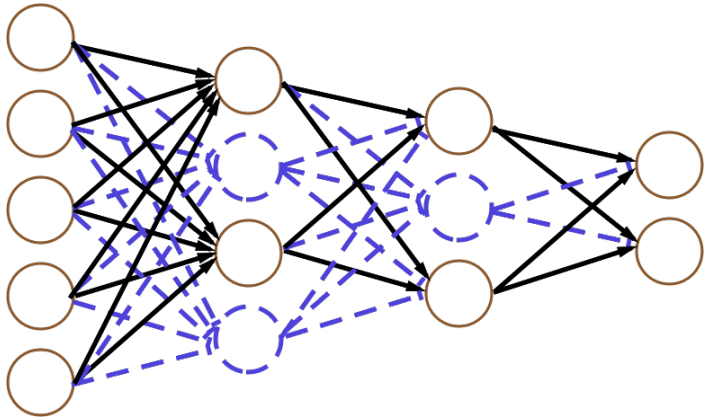
Madry, Aleksander, et al. "Towards deep learning models resistant to adversarial attacks.", ICLR 2018

Compression for CNN



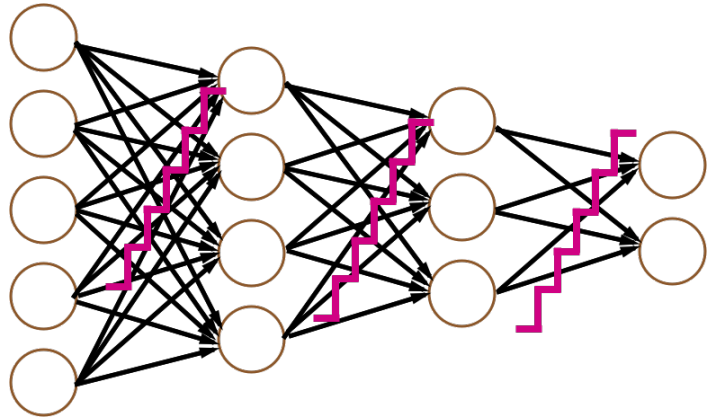
Weight Pruning

[Han et al., NIPS 15]



Node Pruning

[Li et al., ICLR 17]
[He et al., ICCV 17]
[Porikli et al., ECCV 16]



Quantization

[Han et al., ICLR 16]

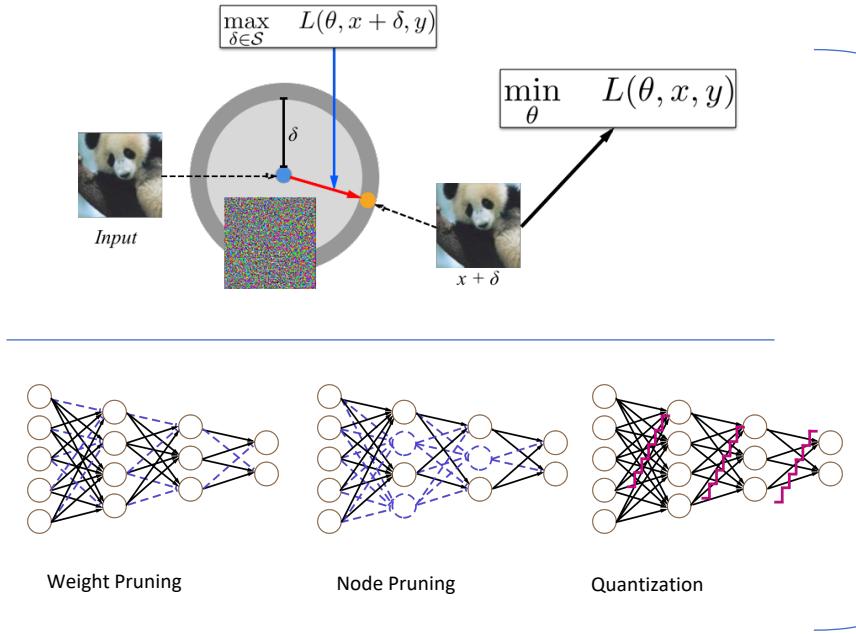
Compression v.s. Robustness

- Highly non-straightforward and contextually varying w.r.t different means of compression
- An appropriately higher CNN model sparsity led to better robustness, whereas over-sparsification could in turn cause more fragility [1]
- [2] showed that sparse algorithms are not stable:
  - If an algorithm promotes sparsity, then its sensitivity to small perturbations fo the input data remains bounded away from zero
  - Quantization seems to reduce the Minimum Description Length and might potentially make the algorithm more robust.
- [3] argued that the tradeoff between robustness and accuracy may be inevitable for the classification task.

[1] Guo et al, "Sparse dnns with improved adversarial robustness", NeurIPS 2018
[2] Xu et al, "Sparse algorithms are not stable: A no-free-lunch theorem". IEEE t-PAMI 2012
[3] Tsipras et al, "Robustness may be at odds with accuracy". Stat, 1050:11, 2018

Adversarially Trained Model Compression (Overall)

- A unified optimization framework for both compression and robustness on CNN



$$\min_{\boldsymbol{\theta}} \quad \sum_{(x,y)\in\mathcal{Z}} f^{\text{adv}}(\boldsymbol{\theta}; x, y) \tag{4}$$

$$\text{s.t.} \quad \underbrace{\sum_{i=1}^{l} \|\boldsymbol{U}^{(i)}\|_0 + \|\boldsymbol{V}^{(i)}\|_0 + \|\boldsymbol{C}^{(i)}\|_0}_{\|\boldsymbol{\theta}\|_0} \leq k, \ \text{(sparsity constraint)}$$

$$\boldsymbol{\theta} \in \mathcal{Q}_b := \{\boldsymbol{\theta} : |\boldsymbol{U}^{(l)}|_0 \leq 2^b, \ |\boldsymbol{V}^{(l)}|_0 \leq 2^b, \ |\boldsymbol{C}^{(l)}|_0 \leq 2^b \ \forall l \in [L]\}. \text{(quantization constraint)}$$

Adversarially Trained Model Compression (Unified Pruning Constraints)

- Sparsification and channel pruning into one constraint

$$\boldsymbol{W} = \boldsymbol{U}\boldsymbol{V} + \boldsymbol{C}, \quad \|\boldsymbol{U}\|_0 + \|\boldsymbol{V}\|_0 + \|\boldsymbol{C}\|_0 \leq k$$

where $||\cdot||_0$ denotes the number of nonzeros of the augment matrix

- The above enforces a novel, compound (including both multiplicative and additive) sparsity structure on W
- UV indicates a natural form of channel pruning
- Such form can be used in the model acceleration with other norm such as L21

Adversarially Trained Model Compression (Non-uniform Quantization)

- Each nonzero element of the DNN parameter can only be chosen from a set of a few values
- These values are not necessarily evenly distributed and need to be optimized
- With respect to the non-uniform quantization strategy, we introduce the quantization constraints

$$|\boldsymbol{U}^{(l)}|_0 \leq 2^b, \ |\boldsymbol{V}^{(l)}|_0 \leq 2^b, \ |\boldsymbol{C}^{(l)}|_0 \leq 2^b \quad \forall l \in [L].$$

Adversarially Trained Model Compression (Adversarial Robustness)

- White-box attack setting: an adversary to eavesdrop the optimization and gradients of the learning model
- When an “clean" image x comes to a target model, “perturb” the image with an adversarial perturbation with bounded magnitudes.

$$B_\infty^\Delta(x) := \{x' : \|x' - x\|_\infty \leq \Delta\}$$

- The training objective for the attacker

$$f^{\text{adv}}(\boldsymbol{\theta}; x, y) = \max_{x' \in B_\infty^\Delta(x)} f(\boldsymbol{\theta}; x', y)$$

- Defensive objective for ATMC

$$\min_{\boldsymbol{\theta}} \sum_{(x,y)\in\mathcal{Z}} f^{\text{adv}}(\boldsymbol{\theta}; x, y).$$

Optimization for ATMC

- Apply ADMM to solve the optimization problem
- Update x^{adv}: $x^{\text{adv}} \leftarrow \text{Proj}_{\{x':\|x'-x\|_\infty \leq \Delta\}} \{x + \alpha \nabla_x f(\boldsymbol{\theta}; x, y)\}$
- Update θ: $\min_{\boldsymbol{\theta}} \quad f(\boldsymbol{\theta}; x^{\text{adv}}, y) + \frac{\rho}{2}\|\boldsymbol{\theta} - \boldsymbol{\theta}' + \boldsymbol{u}\|_F^2 \quad \text{s.t. } \|\boldsymbol{\theta}\|_0 \leq k.$
  - Only related to the sparsity constraint

$$\boldsymbol{\theta} \leftarrow \text{Proj}_{\{\boldsymbol{\theta}'':\|\boldsymbol{\theta}''\|_0 \leq k\}} \left(\boldsymbol{\theta} - \gamma \nabla_{\boldsymbol{\theta}} \left[f(\boldsymbol{\theta}; x^{\text{adv}}, y) + \frac{\rho}{2}\|\boldsymbol{\theta} - \boldsymbol{\theta}' + \boldsymbol{u}\|_F^2\right]\right)$$

- Update θ': $\min_{\boldsymbol{\theta}'} \quad \|\boldsymbol{\theta}' - (\boldsymbol{\theta} + \boldsymbol{u})\|_F^2, \quad \text{s.t. } \boldsymbol{\theta}' \in \mathcal{Q}_b$
  - Only related to quantization constraint
  - For example, essentially solving

$$\min_{\boldsymbol{U}, \{\boldsymbol{a}_k\}_{k=1}^{2^b}} \quad \|\boldsymbol{U} - \bar{\boldsymbol{U}}\|^2 \quad \text{s.t.} \quad \boldsymbol{U}_{i,j} \in \{0, \boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_{2^b}\}$$

  - Lloyd's algorithm [1]

$$\boldsymbol{U}_t'^{(l)} = \text{ZeroKmeans}_{2^b}(\boldsymbol{U}^{(l)} + \boldsymbol{u}_{\boldsymbol{U}^{(l)}})$$

[1] Lloyd, "Least squares quantization in pcm", IEEE transactions on information theory, 1982

Optimization for ATMC

Algorithm 1 ZeroKmeans$_B(\bar{U})$

Input: a set of real numbers $\bar{\boldsymbol{U}}$, number of clusters B.
Output: quantized tensor $\boldsymbol{U}$.
Initialize $\boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_B$ by randomly picked nonzero elements from $\bar{\boldsymbol{U}}$.
$\boldsymbol{Q} := \{0, \boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_B\}$
repeat
  for $i = 0$ to $|\bar{\boldsymbol{U}}| - 1$ **do**
    $\delta_i \leftarrow \arg\min_j (\bar{\boldsymbol{U}}_i - \boldsymbol{Q}_j)^2$
  end for
  Fix $\boldsymbol{Q}_0 = 0$
  for $j = 1$ to B **do**
    $\boldsymbol{a}_j \leftarrow \frac{\sum_i \mathbf{I}(\delta_i = j)\bar{\boldsymbol{U}}_i}{\sum_i \mathbf{I}(\delta_i = j)}$
  end for
until Convergence
for $i = 0$ to $|\bar{\boldsymbol{U}}| - 1$ **do**
  $\boldsymbol{U}_i \leftarrow \boldsymbol{Q}_{\delta_i}$
end for

Algorithm 2 ATMC

Input: dataset $\mathcal{Z}$, stepsize sequence $\{\gamma_t > 0\}_{t=0}^{T-1}$, update steps n and T, hyper-parameter ρ, k, and b, Δ
Output: model $\boldsymbol{\theta}$
$\alpha \leftarrow 1.25 \times \Delta / n$
Initialize θ, let $\boldsymbol{\theta}' = \boldsymbol{\theta}$ and $\boldsymbol{u} = 0$
for $t = 0$ **to** $T - 1$ **do**
  Sample (x, y) from $\mathcal{Z}$
  for $i = 0$ to $n - 1$ **do**
    $x^{\text{adv}} \leftarrow \text{Proj}_{\{x' : \|x' - x\|_\infty \le \Delta\}} \{x + \alpha \nabla_x f(\boldsymbol{\theta}; x, y)\}$
  end for
  $\boldsymbol{\theta} \leftarrow \text{Proj}_{\{\boldsymbol{\theta}'' : \|\theta''\|_0 \le k\}} \big(\boldsymbol{\theta} - \gamma_t \nabla_{\boldsymbol{\theta}} [f(\boldsymbol{\theta}; x^{\text{adv}}, y) + \frac{\rho}{2} \|\boldsymbol{\theta} - \boldsymbol{\theta}' + \boldsymbol{u}\|_F^2]\big)$
  $\boldsymbol{\theta}' \leftarrow \text{ZeroKmeans}_{2^b}(\boldsymbol{\theta} + \boldsymbol{u})$
  $\boldsymbol{u} \leftarrow \boldsymbol{u} + (\boldsymbol{\theta} - \boldsymbol{\theta}')$
end for

Empirical Study

- Datasets and Benchmark Models
  - Four popular image classification datasets
  - Pick one top-performer CNN model on each

Table 1: The datasets and CNN models used in the experiments.

Models	#Parameters	bit width	Model Size (bits)	Dataset & Accuracy
LeNet	430K	32	13,776,000	MNIST: 99.32%
ResNet34	21M	32	680,482,816	CIFAR-10: 93.67%
ResNet34	21M	32	681,957,376	CIFAR-100: 73.16%
WideResNet	11M	32	350,533,120	SVHN: 95.25%

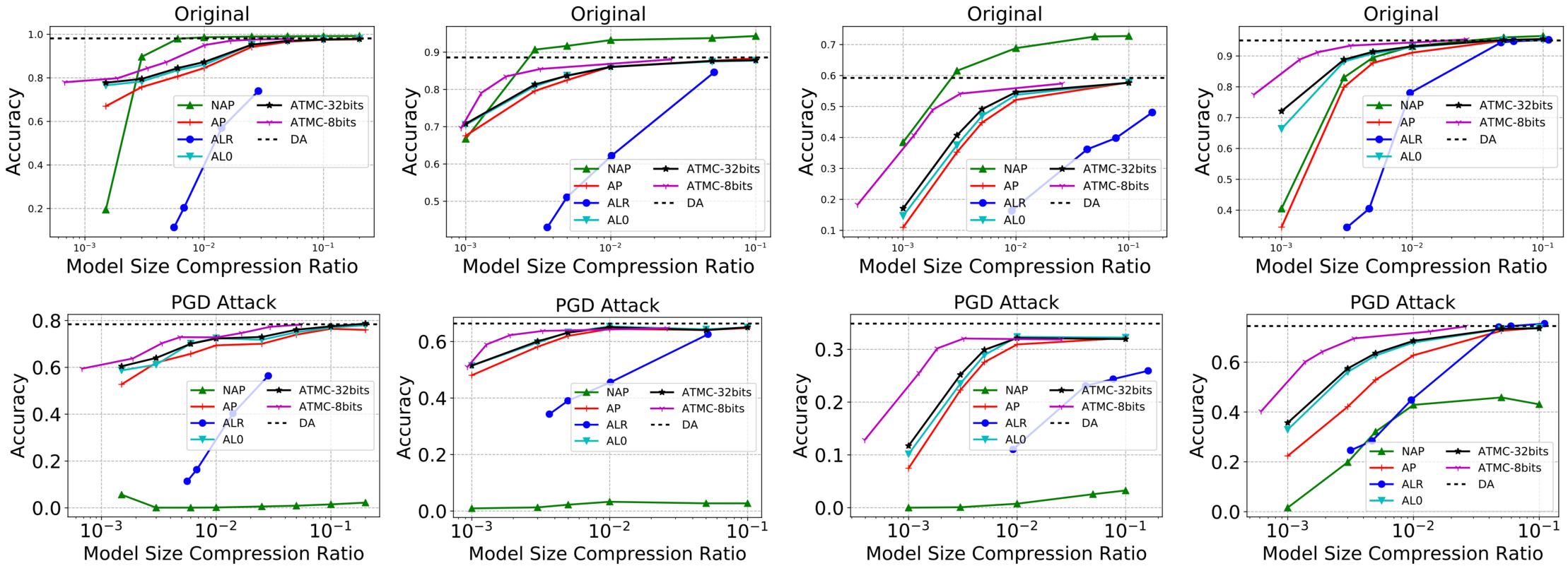
Empirical Study

- Evaluation Metrics
  - Classification accuracies on both benign and on attacked testing sets are reported
- Model Size
  - multiplying the quantization bit per element with the total number of non-zero elements, added with the storage size for the quantization thresholds
- Compression Ratio
  - the ratio between the compressed and original model sizes
- Adversarial Attack Settings
  - PGD attack with the same settings as used in adversarial training on testing sets to evaluate model robustness

Empirical Study

- Baselines
  - Non-adversarial Pruning (NAP)
  - Dense Adversarial Training (DA)
  - Adversarial Pruning (AP)
  - Adversarial l0 Pruning (Al0)
  - Adversarial Low-Rank Decomposition (ALR)
  - ATMC (8bits, 32 bits)
- Comparison on same compression ratio

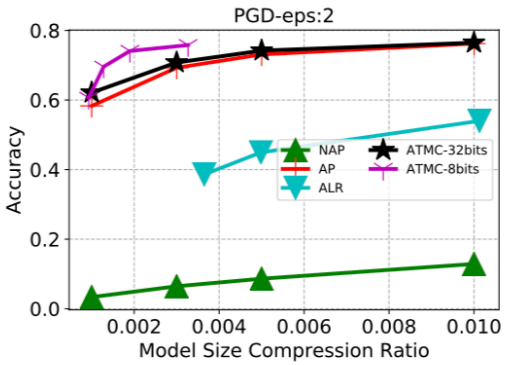
Empirical Study



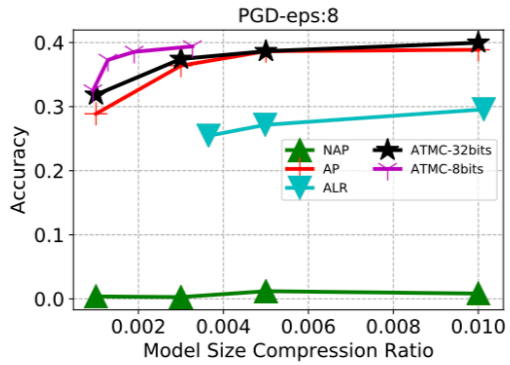
(a) MNIST (b) CIFAR-10 (c) CIFAR-100 (d) SVHN

Empirical Study

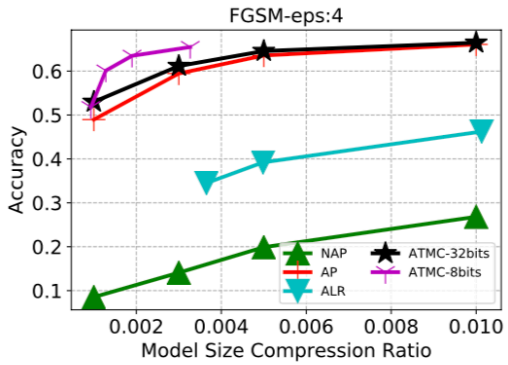
- ATMC also maintains robustness under different adversarial attacks



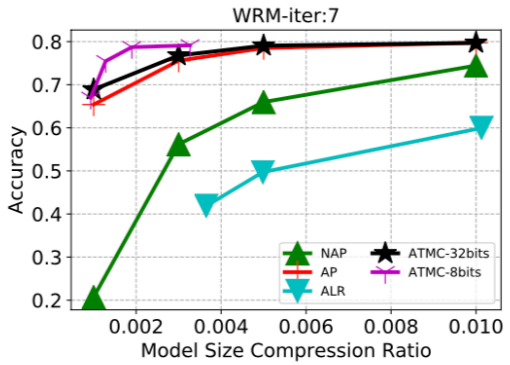
(a) PGD, perturbation=2



(b) PGD, perturbation=8



(c) FGSM, perturbation=4

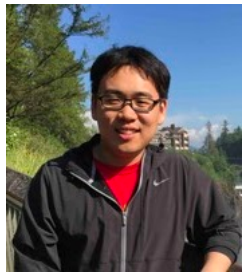


(d) WRM, penalty=1.3, iteration=7

Conclusion

- We propose the ATMC framework, by integrating the two goals, model compression and robustness in one unified constrained optimization framework
- Our extensive expriments endorse the effectiveness of ATMC
  - Naïve model compression may hurt robustness, if the latter is not explicitly taken into account
  - A proper joint optimization could achieve both well
  - A properly compressed model could even maintain almost the same accuracy and robustness compared to the original one

Thanks



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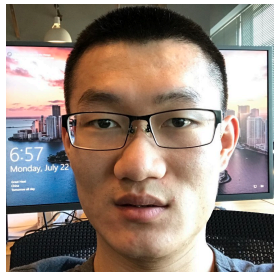

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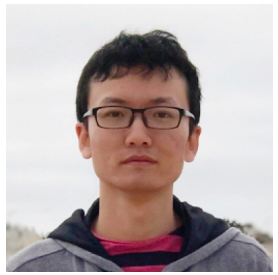
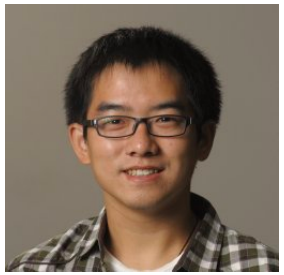


Haichuan Yang

Chen Yu



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