
# Efficient Neural Network Compression

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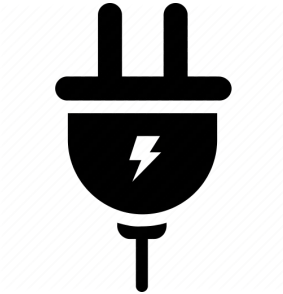
# A Challenge in Deep Learning: *Overparameterization*

Large neural networks require:

memory & computations



power consumption

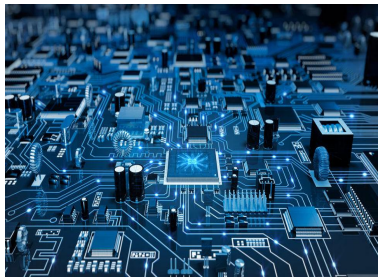
# A Challenge in Deep Learning: *Overparameterization*

Large neural networks require:

memory & computations

power consumption

Critical to resource constrained environments

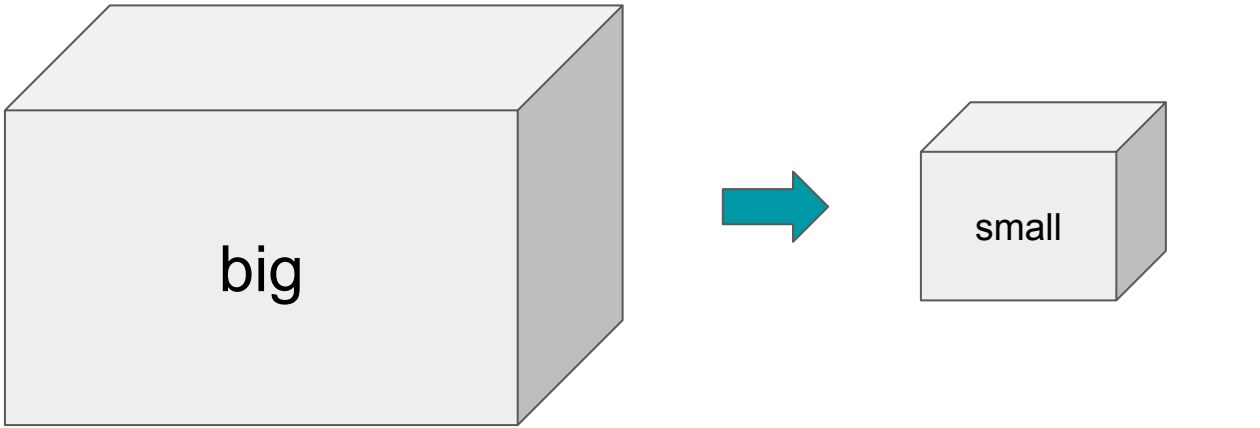


embedded systems
e.g., mobile devices


real-time tasks
e.g., autonomous car

# Network compression

The goal is to reduce the ***size*** of neural network without compromising accuracy.




~ same accuracy

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- Parameters (weights, biases)
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- Magnitude based
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- Bayesian

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⇒ remove > 90% parameters

# Drawbacks in existing approaches

- Hyperparameters with weakly grounded heuristics

  (*e.g.,* layer-wise threshold [5], stochastic pruning rule [2])

**References**
[1] Learning both weights and connections for efficient neural network, Han et al. NIPS'15
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[6] Learning Sparse Neural Networks through L0 Regularization, Louizos et al. ICLR'18

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  ([1,2,3,4,5,6]; almost all)

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***poor scalability & utility***


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No hyperparameters

No iterative prune -- retrain cycle

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***Single-shot pruning prior to training***


# SNIP: Single-shot Network Pruning based on Connection Sensitivity

N. Lee, T. Ajanthan, P. Torr

*International Conference on Learning Representations* (*ICLR*) *2019*

# Objective

- Identify important parameters in the network and remove unimportant ones

$$\min_{\mathbf{w}} L(\mathbf{w}; \mathcal{D}) = \min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^{n} \ell(\mathbf{w}; (\mathbf{x}_i, \mathbf{y}_i)) \ ,$$
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- Measure the effect of removing each parameter on the loss

$$\Delta L_j(\mathbf{w}; \mathcal{D}) = L(\mathbf{1} \odot \mathbf{w}; \mathcal{D}) - L((\mathbf{1} - \mathbf{e}_j) \odot \mathbf{w}; \mathcal{D}) \,,$$

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- The greedy way is prohibitively expensive to perform: $O(m!)$

# SNIP

The effect on the loss can be approximated by

1. auxiliary variables representing the connectivity of parameters
2. derivative of the loss w.r.t. these indicator variables

# SNIP

1. Introduce c

$$\min_{\mathbf{c},\mathbf{w}} L(\mathbf{c} \odot \mathbf{w}; \mathcal{D}) = \min_{\mathbf{c},\mathbf{w}} \frac{1}{n} \sum_{i=1}^{n} \ell(\mathbf{c} \odot \mathbf{w}; (\mathbf{x}_i, \mathbf{y}_i)) \ ,$$
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2. Derivative w.r.t. c

$$\Delta L_j(\mathbf{w}; \mathcal{D}) \approx g_j(\mathbf{w}; \mathcal{D}) = \left. \frac{\partial L(\mathbf{c} \odot \mathbf{w}; \mathcal{D})}{\partial c_j} \right|_{\mathbf{c}=\mathbf{1}} = \lim_{\delta \to 0} \left. \frac{L(\mathbf{c} \odot \mathbf{w}; \mathcal{D}) - L((\mathbf{c} - \delta\, \mathbf{e}_j) \odot \mathbf{w}; \mathcal{D})}{\delta} \right|_{\mathbf{c}=\mathbf{1}}$$

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- ∂L/∂cj is an infinitesimal version of ΔLj
- measures the rate of change of L w.r.t. infinitesimal change in cj from 1 → 1 − δ
- computed efficiently in one forward-backward pass using auto differentiation, for all j at once

Reference: Understanding black-box predictions via influence functions, Koh & Liang. ICML'17

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3. Connection sensitivity

$$s_j = \frac{|g_j(\mathbf{w}; \mathcal{D})|}{\sum_{k=1}^{m} |g_k(\mathbf{w}; \mathcal{D})|} \; .$$

# Prune at initialization

- Measure CS on untrained networks prior to training

  → Or zero gradients at pretrained

- Sample weights from a dist. with architecture aware variance

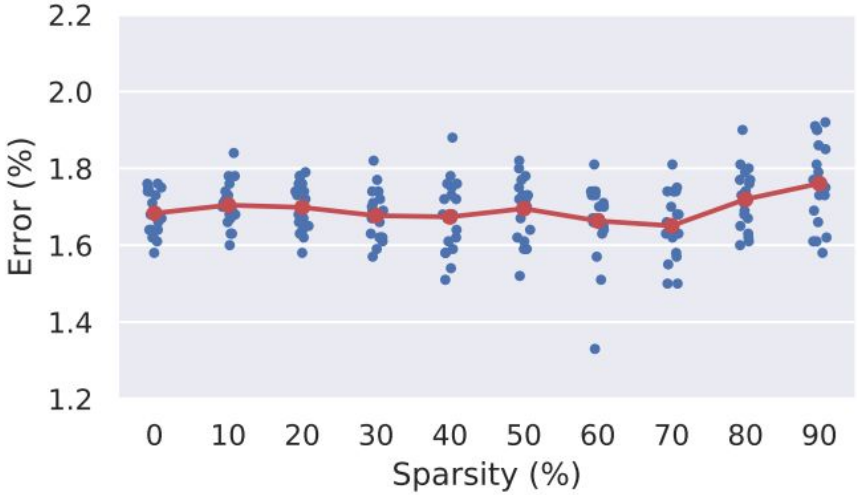
  → Ensure the variance of weights to remain throughout the network ([1])

- Alleviate the dependency on the weights in computing CS

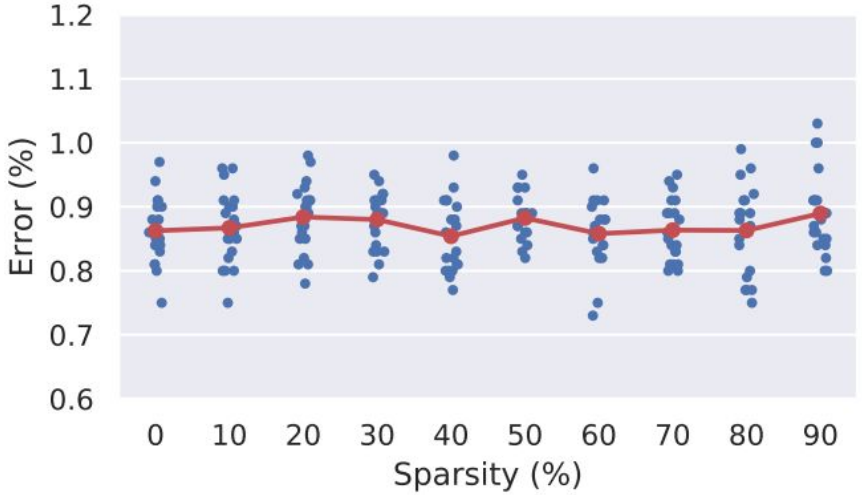
  → Remove the pretraining requirement, architecture dep. hyperparameters

[1] Understanding the difficulty of training deep feedforward neural networks, Glorot & Bengio, AISTATS 2010

# LeNets




(a) LeNet-300-100




(b) LeNet-5-Caffe

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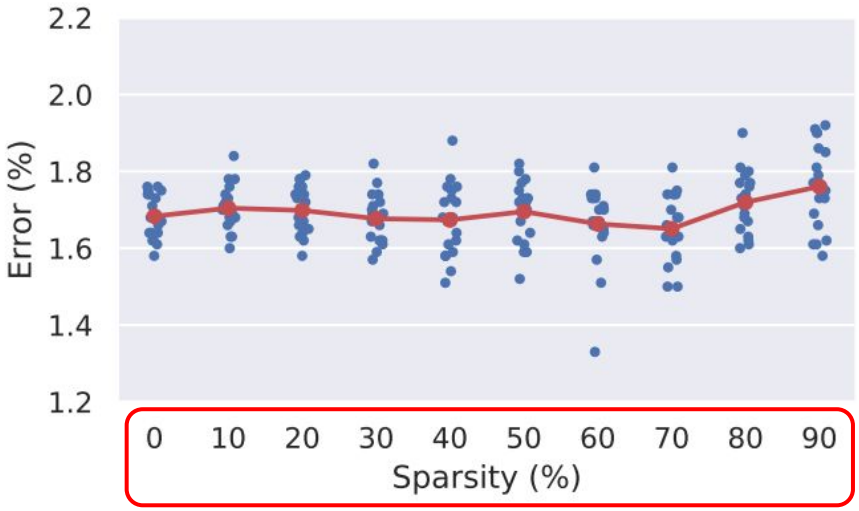


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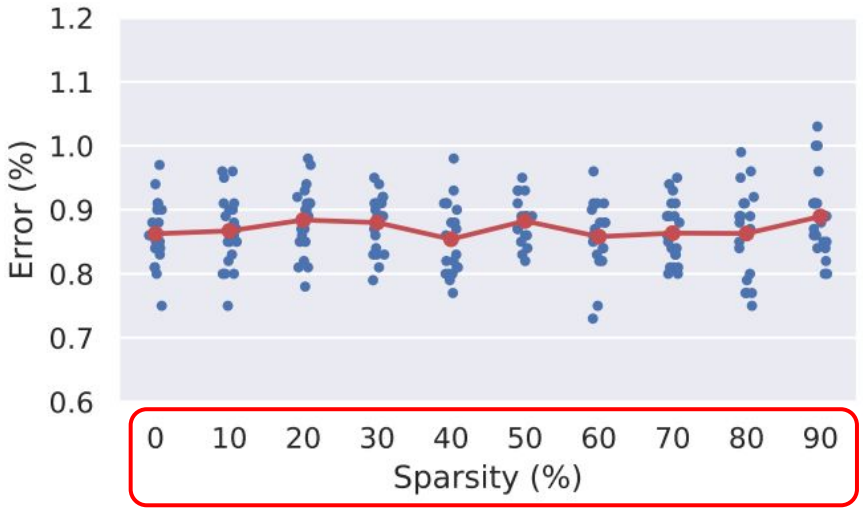


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# LeNets: comparison to SOTA

| Method | Criterion | LeNet-300-100 $\bar{\kappa}$ (%) | LeNet-300-100 err. (%) | LeNet-5-Caffe $\bar{\kappa}$ (%) | LeNet-5-Caffe err. (%) | Pretrain | # Prune | Additional hyperparam. | Augment objective | Arch. constraints |
|---|---|---|---|---|---|---|---|---|---|---|
| Ref. | – | – | 1.7 | – | 0.9 | – | – | – | – | – |
| LWC | Magnitude | 91.7 | **1.6** | 91.7 | **0.8** | ✓ | many | ✓ | ✗ | ✓ |
| DNS | Magnitude | 98.2 | 2.0 | 99.1 | 0.9 | ✓ | many | ✓ | ✗ | ✓ |
| LC | Magnitude | 99.0 | 3.2 | 99.0 | 1.1 | ✓ | many | ✓ | ✓ | ✗ |
| SWS | Bayesian | 95.6 | 1.9 | 99.5 | 1.0 | ✓ | soft | ✓ | ✓ | ✗ |
| SVD | Bayesian | 98.5 | 1.9 | 99.6 | **0.8** | ✓ | soft | ✓ | ✓ | ✗ |
| OBD | Hessian | 92.0 | 2.0 | 92.0 | 2.7 | ✓ | many | ✓ | ✗ | ✗ |
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| SNIP (ours) | Connection sensitivity | 95.0<br>98.0 | **1.6**<br>2.4 | 98.0<br>99.0 | **0.8**<br>1.1 | ✗ | **1** | ✗ | ✗ | ✗ |

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# Various architectures & models

| Architecture | Model | Sparsity (%) | # Parameters | Error (%) | Δ |
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| Convolutional | AlexNet-s | 90.0 | 5.1m → 507k | 14.12 → 14.99 | +0.87 |
| | AlexNet-b | 90.0 | 8.5m → 849k | 13.92 → 14.50 | +0.58 |
| | VGG-C | 95.0 | 10.5m → 526k | 6.82 → 7.27 | +0.45 |
| | VGG-D | 95.0 | 15.2m → 762k | 6.76 → 7.09 | +0.33 |
| | VGG-like | 97.0 | 15.0m → 449k | 8.26 → 8.00 | **−0.26** |
| Residual | WRN-16-8 | 95.0 | 10.0m → 548k | 6.21 → 6.63 | +0.42 |
| | WRN-16-10 | 95.0 | 17.1m → 856k | 5.91 → 6.43 | +0.52 |
| | WRN-22-8 | 95.0 | 17.2m → 858k | 6.14 → 5.85 | **−0.29** |
| Recurrent | LSTM-s | 95.0 | 137k → 6.8k | 1.88 → 1.57 | **−0.31** |
| | LSTM-b | 95.0 | 535k → 26.8k | 1.15 → 1.35 | +0.20 |
| | GRU-s | 95.0 | 104k → 5.2k | 1.87 → 2.41 | +0.54 |
| | GRU-b | 95.0 | 404k → 20.2k | 1.71 → 1.52 | **−0.19** |

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| | GRU-s | 95.0 | 104k → 5.2k | 1.87 → 2.41 | +0.54 |
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# Various architectures & models

| Architecture | Model | Sparsity (%) | # Parameters | Error (%) | Δ |
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| | VGG-C | 95.0 | 10.5m → 526k | 6.82 → 7.27 | +0.45 |
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| | VGG-like | 97.0 | 15.0m → 449k | 8.26 → 8.00 | **−0.26** |
| Residual | WRN-16-8 | 95.0 | 10.0m → 548k | 6.21 → 6.63 | +0.42 |
| | WRN-16-10 | 95.0 | 17.1m → 856k | 5.91 → 6.43 | +0.52 |
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Carrying out such inspection is not straightforward with other methods.

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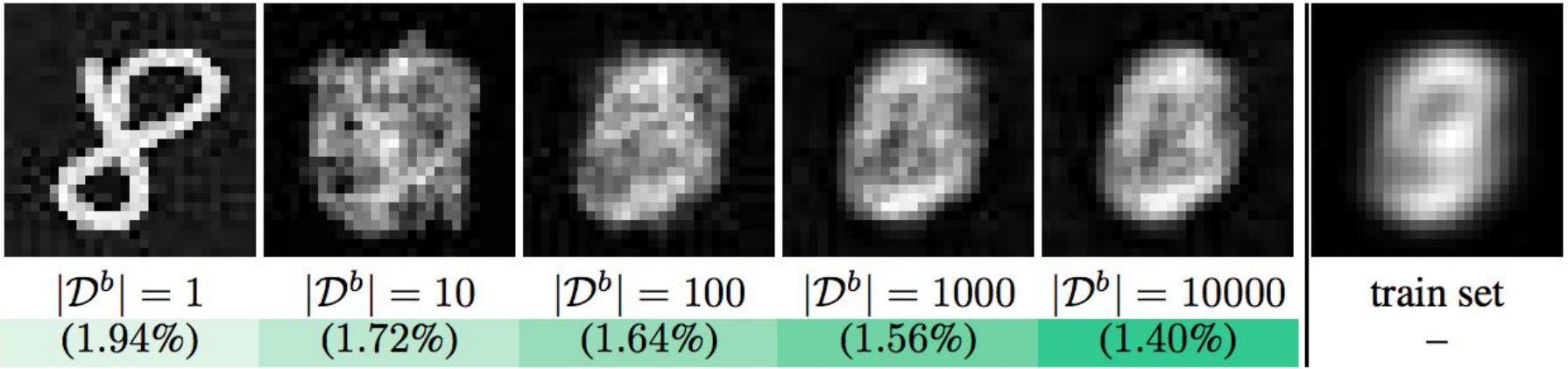


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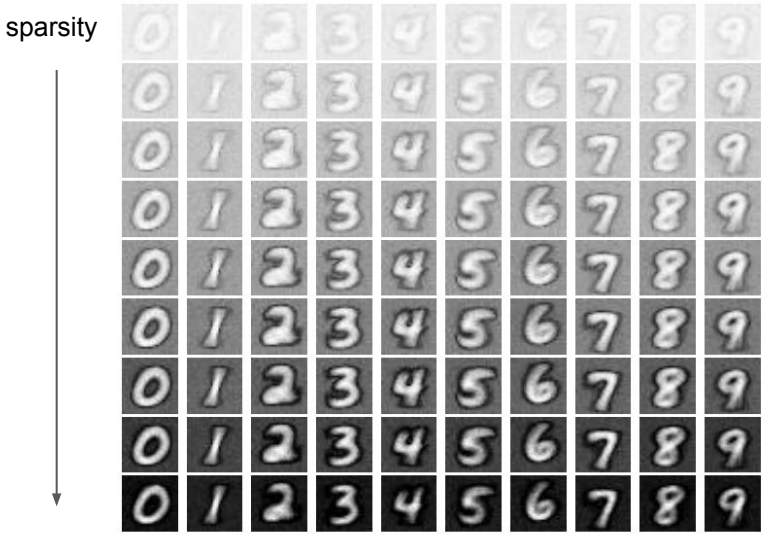
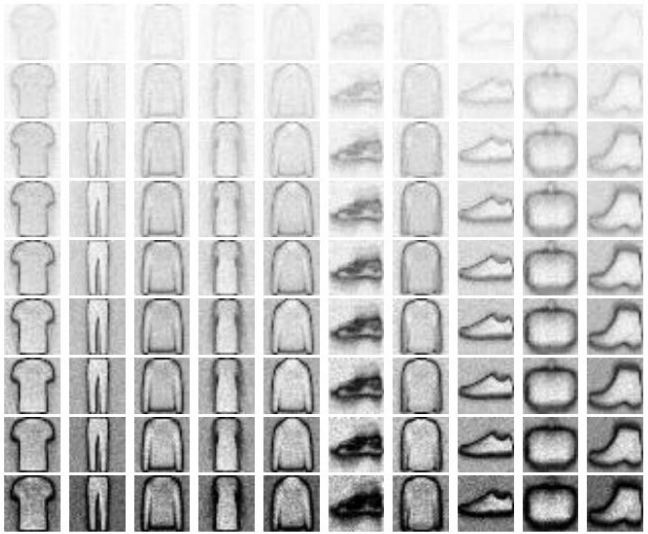


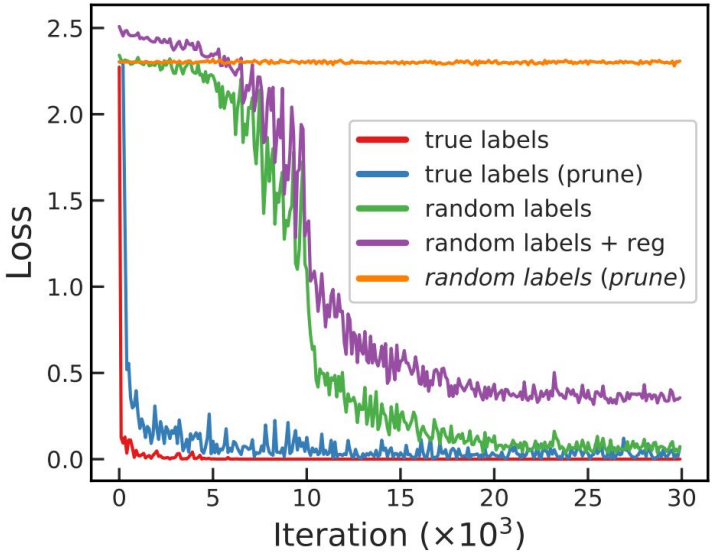

(a) MNIST



(b) Fashion-MNIST

The parameters connected to the discriminative part of image are retained.

# Prevent memorization




**[Fitting random labels]**
Understanding deep learning requires rethinking generalization, Zhang et al. ICLR'17

The pruned network does not have sufficient capacity to fit the random labels, but is capable of performing the task.

# SNIP

Simple
Versatile
Interpretable

**Paper:**
https://arxiv.org/abs/1810.02340

**Code:**
https://github.com/namhoonlee/snip-public

**Contact:**
http://www.robots.ox.ac.uk/~namhoon/