AutoPrune: Automatic Network Pruning by Regularizing Auxiliary Parameters

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Abstract

Reducing the model redundancy is an important task to deploy complex deep learning models to **resource-limited or time-sensitive devices**. Directly regularizing or modifying weight values makes pruning procedure less robust. To build a easy-to-use pruning method, we propose **AutoPrune**, which prunes the network through optimizing a set of **trainable auxiliary parameters** instead of original weights. The instability and noise during training on auxiliary parameters will not directly affect weight values, which makes pruning process more **robust to noise and less sensitive to hyperparameters**. Moreover, we design gradient update rules for auxiliary parameters to keep them **consistent** with pruning tasks. Our method can automatically eliminate network redundancy with **recoverability**, relieving the complicated prior knowledge required to design thresholding functions.

Application domains: *wearable devices, automatic driving, IoT devices*

Motivation

Benefits of a Pruned Light-Weight Neural Network:

- **Smaller size**: Reduce the model size and easy to store
- **Faster inference**: Accelerate model prediction/inference speed
- **Faster training**: Shrink training time for real time deployment
- **Same accuracy**: Slim a complicated model without accuracy drop

Limitations of State-of-the-Art Models:

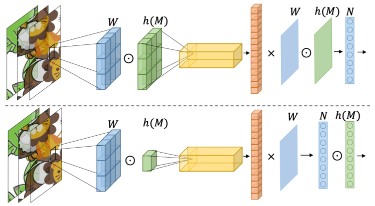
- **Necessary expert knowledge**: Prior knowledge is required to tune different hyperparameters for different models.
- **Unstable pruning process**: Pruning directly on weights/neurons makes pruning less robust and sensitive to hyperparameters.

Contribution

1) We offer a gradient **based automatic network pruning model**;
2) we propose **novel and weakly coupled update rule** for auxiliary parameters to stabilize pruning procedure;
3) we **reduce the sub-graph discrepancy** by iteratively evaluating recoverable sub-graph;
4) we evaluate different **smooth approximations** of the derivative of the rectifier;
5) we obtain the state-of-art results on both **structure and weight pruning** and our method is **scalable** on modern models and datasets.

Methods

Pruning framework:

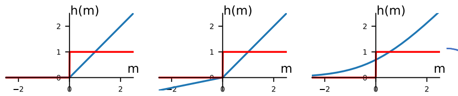


Problem formulation:

$$\min_{w} \mathcal{L}_1 = \min_{w} \sum_{i=1}^{N} \mathcal{L}(f(x_i, W \odot h(M)), y_i) + \lambda \mathcal{R}(W),\ x_i \in X_{train},$$

$$\min_{m} \mathcal{L}_2 = \min_{m} \sum_{i=1}^{N} \mathcal{L}(f(x_i, W \odot h(M)), y_i) + \mu \mathcal{R}(h(M)),\ x_i \in X_{val},$$

Different substitute gradient:



Update auxiliary parameters:

$$m_{ij} := m_{ij} - \eta\left(\frac{\partial \mathcal{L}_{acc}}{\partial t_{ij}} sgn(w_{ij}) \frac{\partial h(m_{ij})}{\partial m_{ij}}\right) - \mu \frac{\partial h(m_{ij})}{\partial m_{ij}}$$

- **Sensitivity Consistency:** Smaller the weight, more sensitive the corresponding auxiliary parameter. $\frac{\partial \mathcal{L}_{acc}}{\partial m_{ij}} \propto \frac{1}{f(|w_{ij}|)}$
- **Correlation Consistency**: The gradient of an arbitrary auxiliary parameter is the same as the direction of the gradient of its corresponding weight.
$$sgn(\frac{\partial \mathcal{L}_2}{\partial m_{ij}}) = sgn(\frac{\partial \mathcal{L}_1}{\partial |w_{ij}|})$$
- **Direction Consistency:** The inner product between the expected coarse and population gradients is greater than zero.

Recoverable pruning:

- Follow the idea of Dynamic Network Surgery.
- Incorrectly pruned weights will be recovered to compensate for the increase of loss.
- Reduce discrepancy between parent graph and child graph.

Experiments

Neuron Pruning:

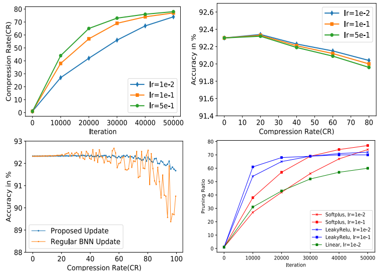
Table 1: Comparison of Different Neuron Pruning Techniques

Model	Methods	Base Error	Error	Epochs	Neurons per Layer	NCR	FLOPs
LeNet-300-100 784-300-100	Louizos *et al.* [2017]	1.60%	1.80%	-	278-98-13	3.04	11%
	Louizos *et al.* [2018]	-	**1.40%**	200	219-214-100	2.22	26%
	Louizos *et al.* [2018]	-	1.80%	200	266-88-33	3.06	10%
	Our method	1.60%	1.82%	**100**	244-85-37	**3.23**	**9%**
LeNet5 (MNIST) 20-50-800-500	Wen *et al.* [2016]	-	1.00%	-	3-12-800-500	1.04	25%
	Neklyudov *et al.* [2017]	-	0.86%	-	2-18-284-283	2.33	9%
	Louizos *et al.* [2017]	0.90%	1.00%	-	5-10-76-16	12.8	**7%**
	Louizos *et al.* [2018]	-	0.90%	200	20-25-45-462	2.48	50%
	Louizos *et al.* [2018]	-	1.00%	200	9-18-65-25	**11.71**	17%
	Our method	0.78%	**0.80%**	**100**	4-16-86-87	9.86	**7%**
VGG-like (CIFAR-10) 64x2-128x2-256x3-512x7	Li *et al.* [2017]	6.75%	**6.60%**	**40**	32-64-128-128-256-256-256-256-256-256-256-256-256-512	1.49	66%
	Neklyudov *et al.* [2017]	7.20%	7.50%	-	64-62-128-126-234-155-31-79-73-9-59-73-56-27	4.03	43%
	Neklyudov *et al.* [2017]	7.20%	9.00%	-	44-54-92-115-234-155-31-76-55-9-34-35-21-280	3.83	32%
	Our method	7.60%	8.50%	150	37-41-91-89-156-140-74-81-54-51-44-46-48-52	**4.72**	**23%**

Table 3: MobileNetV2(Top 1 Accuracy)

FLOPs	Methods	FLOPs	Accuracy
100M	Sandler *et al.* [2018]	97M	65.40%
	Yu *et al.* [2018]	97M	64.40%
	Yu and Huang [2019b]	97M	65.10%
	Our method	102M	**66.83%**
200M	Sandler *et al.* [2018]	209M	69.80%
	Tan *et al.* [2019]	216	71.5%
	Yu and Huang [2019b]	209M	69.60%
	Wu *et al.* [2019]	246M	73%
	Yu and Huang [2019a]	207M	73%
	Our method	209M	**73.32%**
300M	Sandler *et al.* [2018]	300M	69.80%
	Tan *et al.* [2019]	317M	74%
	Yu and Huang [2019a]	305M	**74.20%**
	Our method	305M	74.0%

Hyperparameter Sensitivity:



Weight Pruning:

Table 4: Comparison of Different Weight Pruning Techniques

Model	Methods	Error	CR
LeNet300-100 (MNIST)	Dong *et al.* [2017]	1.76%→2.43%	66.7
	Ullrich *et al.* [2017]	1.89%→1.94%	64
	Molchanov *et al.* [2017]	1.64%→1.92%	68
	Our method	1.72%→ **1.78%**	**80**
LeNet5 (MNIST)	Guo *et al.* [2016]	0.91%→0.91%	108
	Ullrich *et al.* [2017]	0.88%→0.97%	162
	Molchanov *et al.* [2017]	0.80%→ **0.75%**	280
	Li *et al.* [2018]	0.91%→0.91%	298
	Our method	0.78%→0.80%	260
	Our method	0.91%→0.91%	**310**
VGG-like (CIFAR-10)	Zhuang *et al.* [2018]	6.01%→**5.43%**	15.58
	Zhu *et al.* [2018]	6.42%→6.69%	8.5
	Molchanov *et al.* [2017]	7.55%→7.55%	65
	Our method	7.60%→7.82%	**75**
AlexNet (ILSVRC12)	Guo *et al.* [2016]	43.42%→43.09%	17.7
	Srinivas *et al.* [2017]	42.80%→**43.04%**	10.3
	Dong *et al.* [2017]	43.30%→50.04%	9.1
	Our method	43.26%→44.10%	**18.5**
ResNet50 (ILSVRC12)	Zhuang *et al.* [2018]	23.99%→**25.05%**	2.06
	Our method	25.10%→25.50%	**2.2**

References

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