2020 embedded VISION summit

Joint Regularization on Activations and Weights for Efficient Neural Network Pruning

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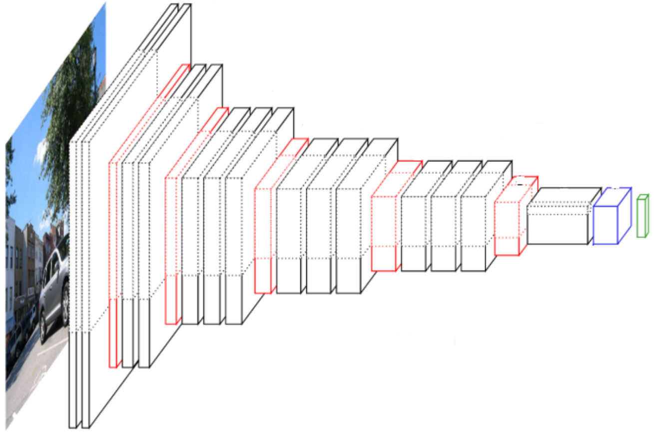
BLACK SESAME TECHNOLOGIES

Neural Network Deployment Challenge

Big network

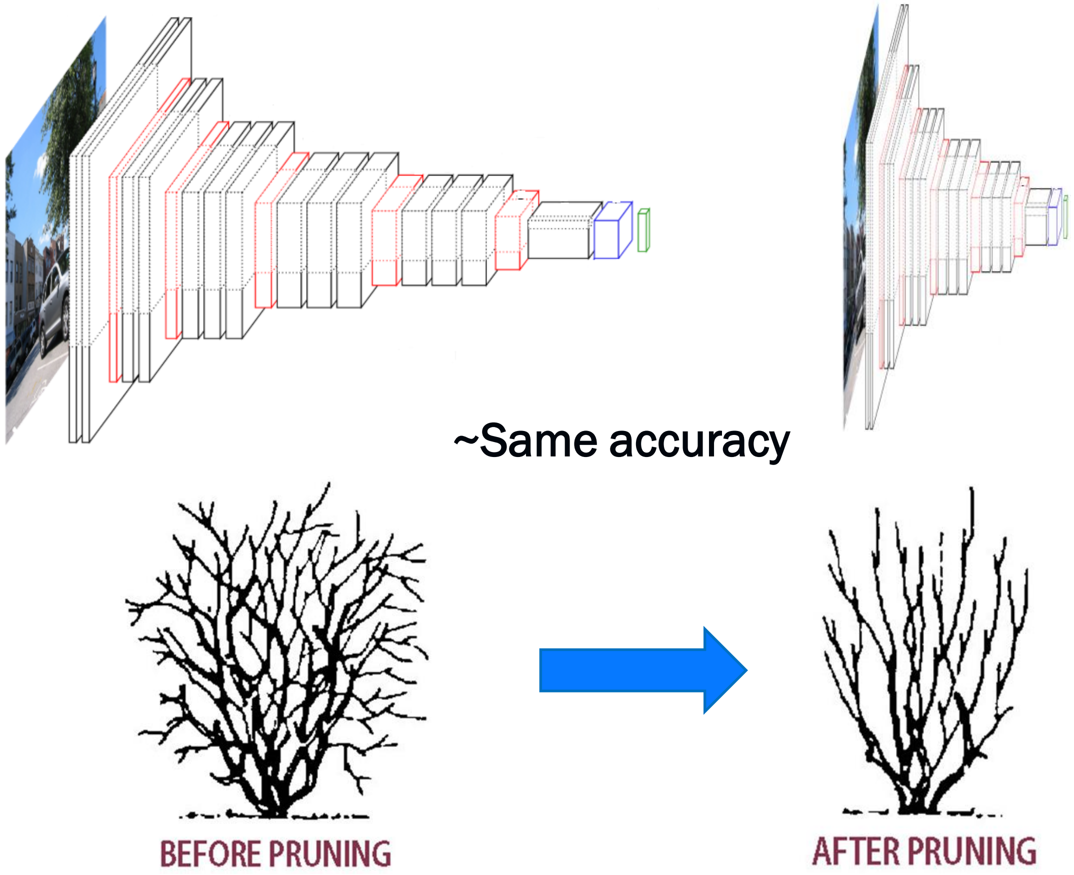


Computation & Memory & Power

Deployment

Embedded system, e.g., autonomous driving

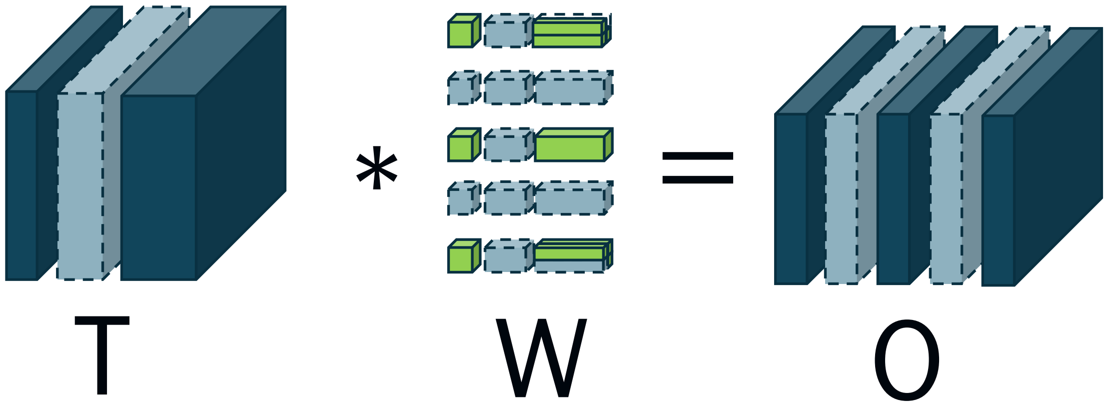
Neural Network Pruning

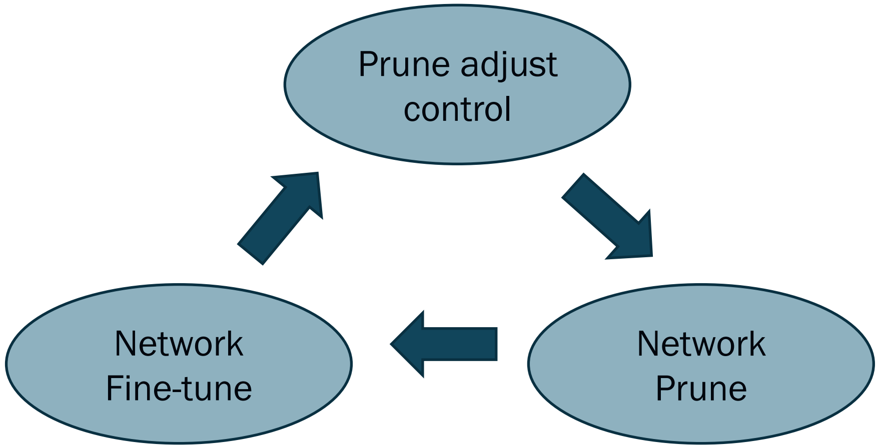


Purposes of network pruning

- Reduce network size
- Improve inference speed
- Deployed on resource constrained platform

Weight Pruning





Magnitude based:

$$m_i = \begin{cases} 1 & if\ |w_i| \geq t \\ 0 & if\ |w_i| < t \end{cases}$$

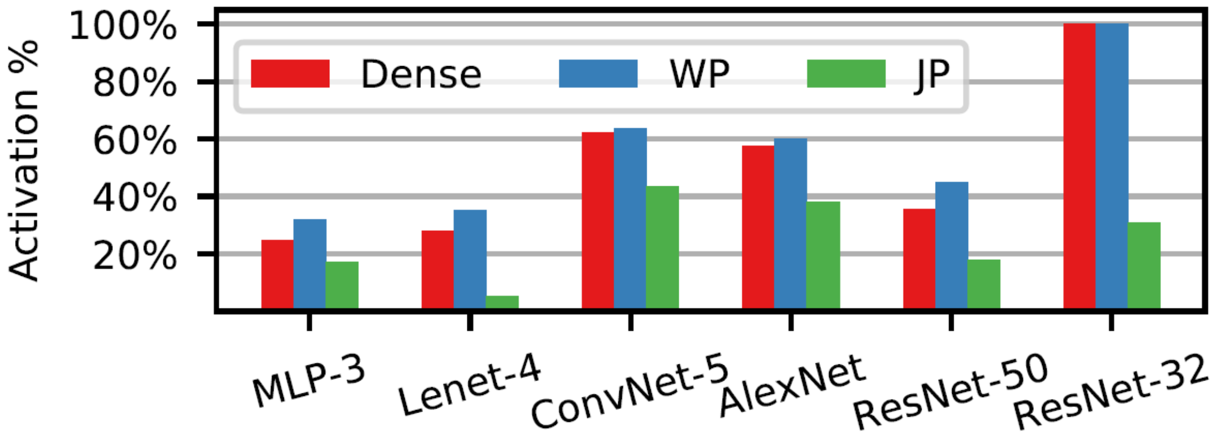
Sensitivity based:

$$m_i = \begin{cases} 1 & if\ \left| w_i \frac{\partial L}{w_i} \right| \geq t \\ 0 & if\ \left| w_i \frac{\partial L}{w_i} \right| < t \end{cases}$$

where m is sparsity mask.

Motivations

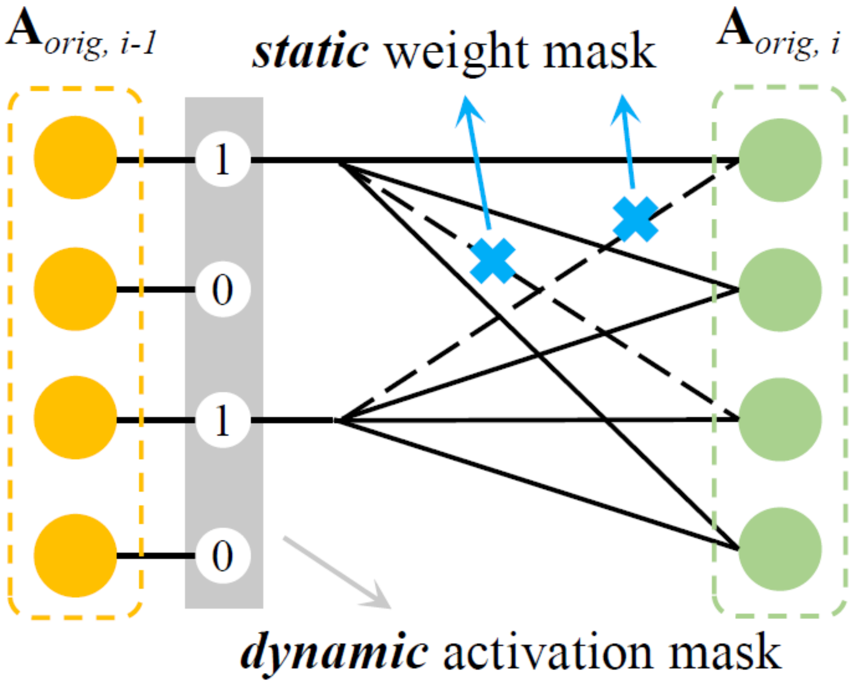
- Activation sparsity could reduce computation as well
- Weight sparsity causes more non-zero activations



* Dense – without pruning
* WP – weight pruning
* JP – weight and activation joint pruning

Joint Regularization for Weights and Activations

Joint Regularization

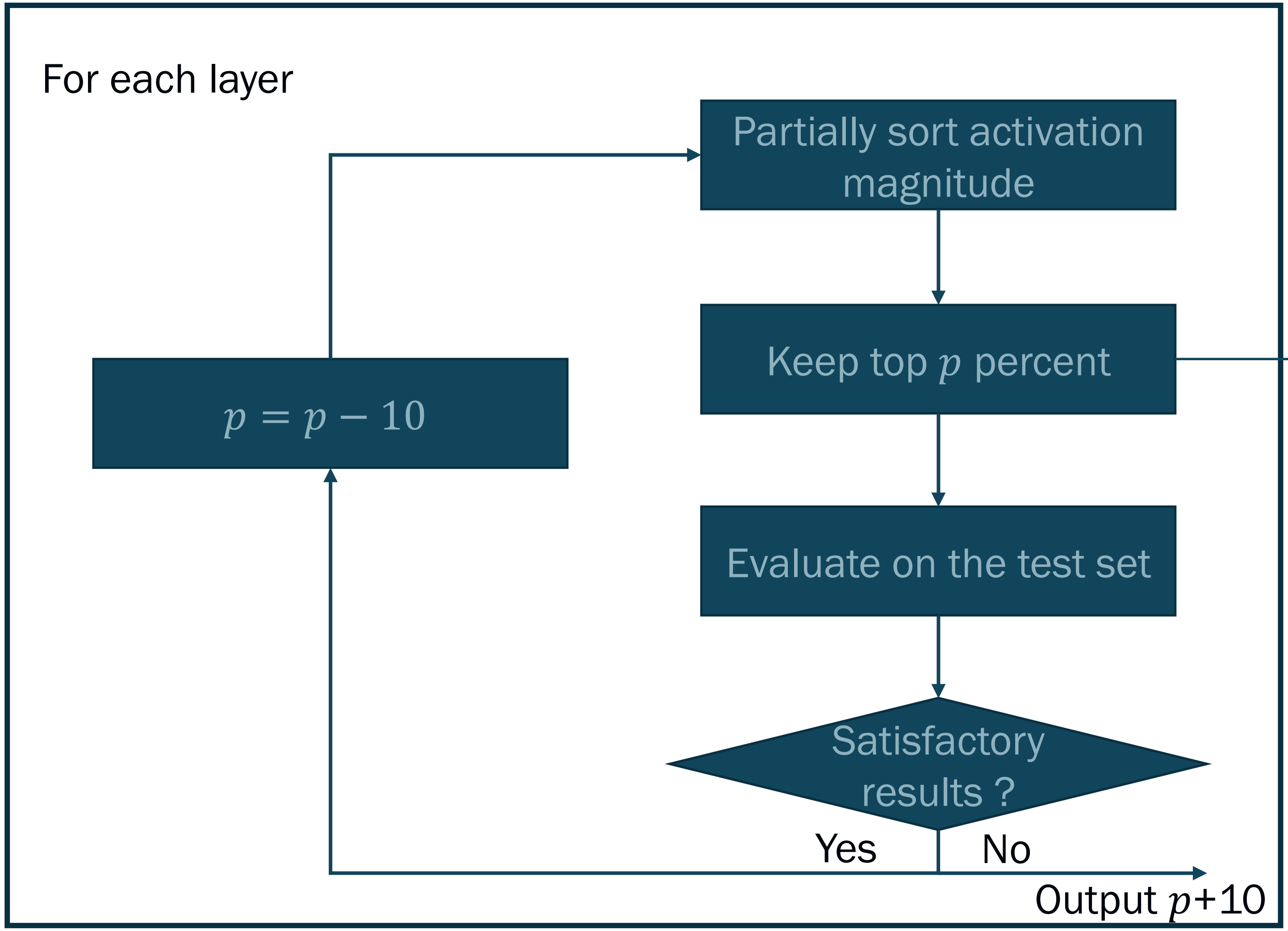


$$Loss = \frac{1}{n}\sum_{k=1}^{n}\mathcal{L}(\mathbf{y}_k, \mathcal{D}(\mathbf{x}_k, \mathbb{S}_W, \mathbb{S}_T)) + \alpha \cdot ||\mathbb{S}_W||_1,$$

$$\mathbb{S}_W^*,\ \mathbb{S}_T^* = \underset{\mathbb{S}_W,\ \mathbb{S}_T}{\operatorname{argmin}}\ \{Loss\}.$$

- Use widely adopted ℓ_1/ℓ_2 regularizers to get **static** weight mask.
- Use projected gradient descent (PGD) method to get **dynamic** ℓ_0 activation mask.
- The **dynamic** mask keeps the N largest elements, while pruning small elements, compared with **static** mask where elements below a given threshold are pruned.

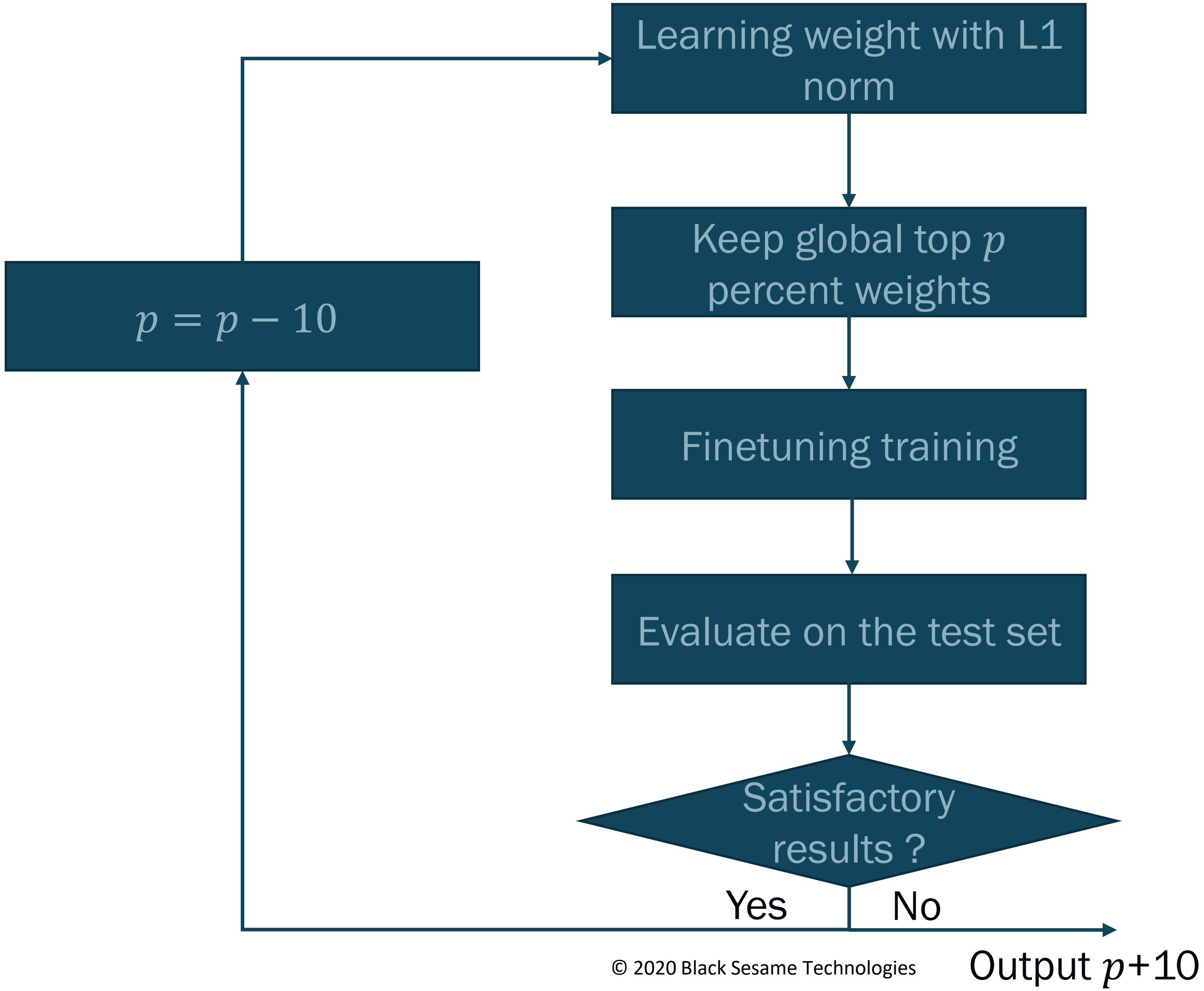
Dynamic Activation Mask



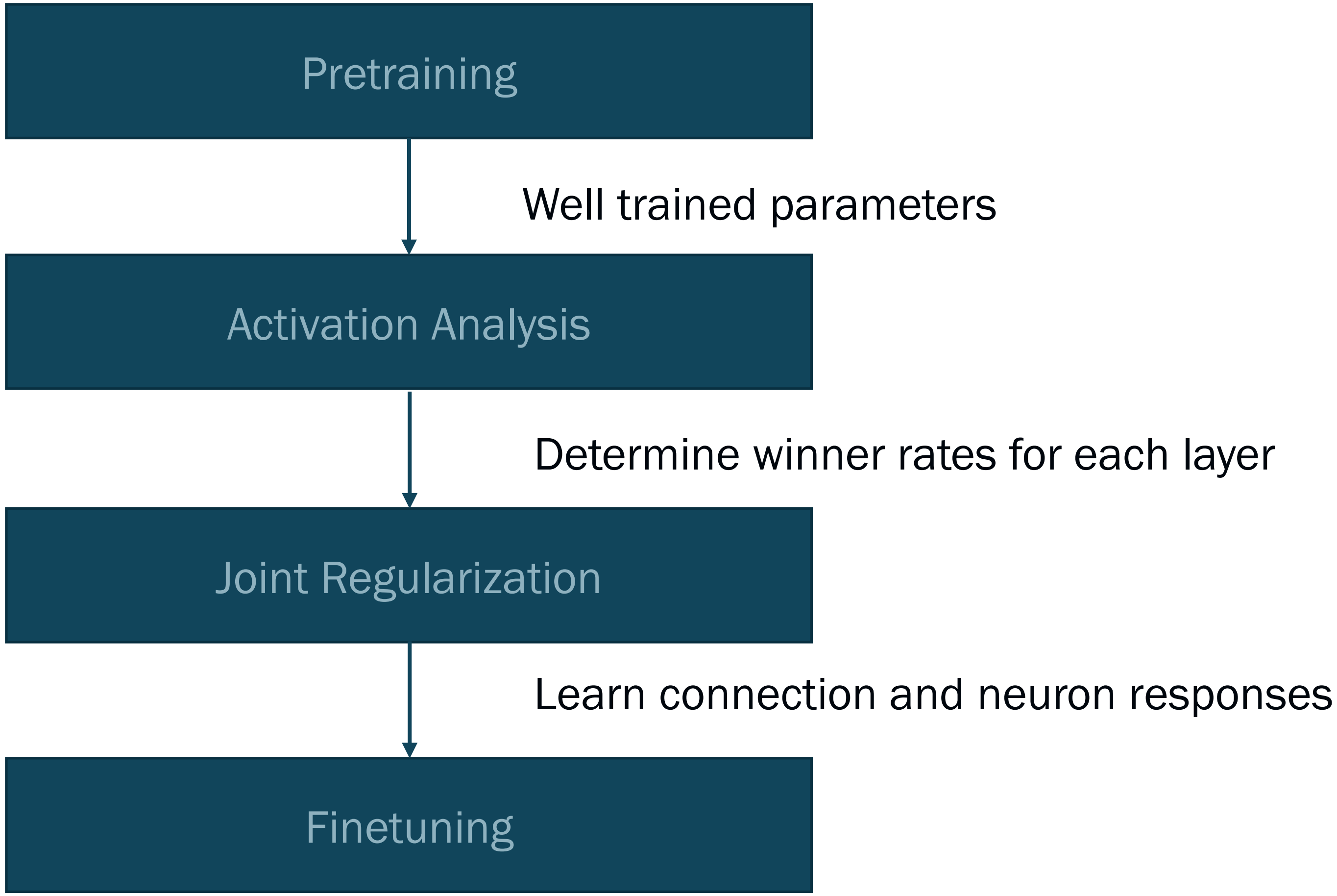
$$a_{m,j} = \begin{cases} a_{orig,j}, & \text{when } \mathbf{abs}(a_{orig,j}) > \theta, \\ 0, & \text{otherwise.} \end{cases}$$

The acceptable results are evaluated against tolerable loss, e.g., 2%

Static Weight Mask



Network Training



Experiments

Applied to Multiple Nets on Multiple Datasets

Compared to the original dense network, within 0.4% accuracy loss:

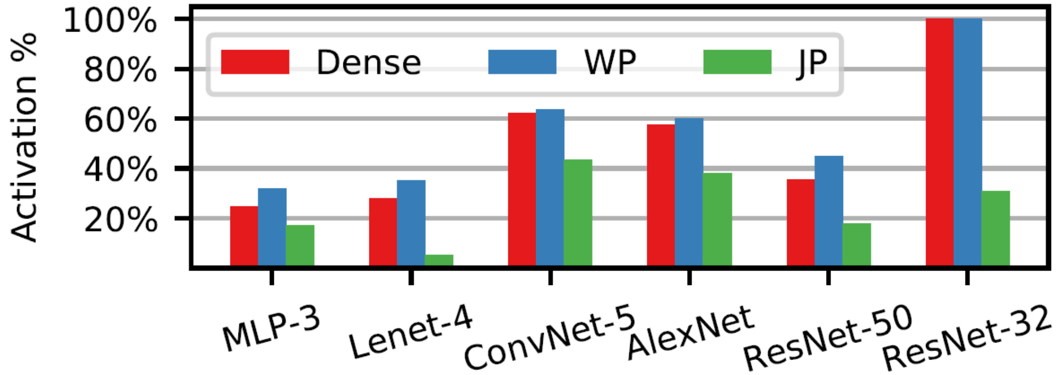
- 1.4x to 5.2x activation compression rate
- 1.6x to 12.3x weight compression rate
- 72.3% to 98.8% MAC reduction

TABLE I
SUMMARY OF JPNETS

Network	MLP-3	Lenet-4	ConvNet-5	AlexNet	ResNet-50	ResNet-32
Dataset	MNIST	MNIST	CIFAR-10	ImageNet	ImageNet	CIFAR-10
Activation Function	ReLU	ReLU	ReLU	ReLU	ReLU	Leaky ReLU
Accuracy Baseline	98.41%	99.4%	86.0%	57.22%	75.6%	95.0%
Accuracy Joint Regularization	98.42%	99.0%	85.9%	57.26%	75.7%	94.6%
Activation Percentage	17.1%	5.5%	43.6%	37.9%	17.7%	30.8%
Weight Compression Rate	10×	12.3×	2.5×	5.3×	1.6×	3.1×
MAC Percentage	3.65%	1.2%	27.7%	25.2%	19.1%	11.5%

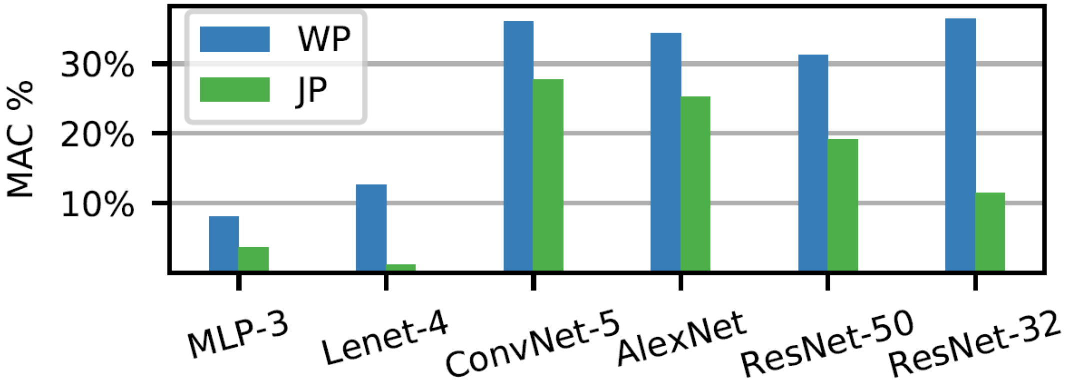
- Activation Percentage: percentage of non-zero activations
- MAC Percentage: percentage relative to dense network

Compared with Weight Pruning Only



(a) Comparison of non-zero activation percentage.

* Percentage relative to total activations



(b) Comparison of MAC percentage.

* Percentage relative to dense network

- The weight pruning based on ℓ_1/ℓ_2 regularization tends to increase the non-zero activation percentage compared to the original dense models.
- JP provides a 1.3× ~ 10.5× improvement compared to WP only by remove 7.7% ~ 22.5% more activations.
- JP also works on non-ReLU activation function, like in ResNet-32.

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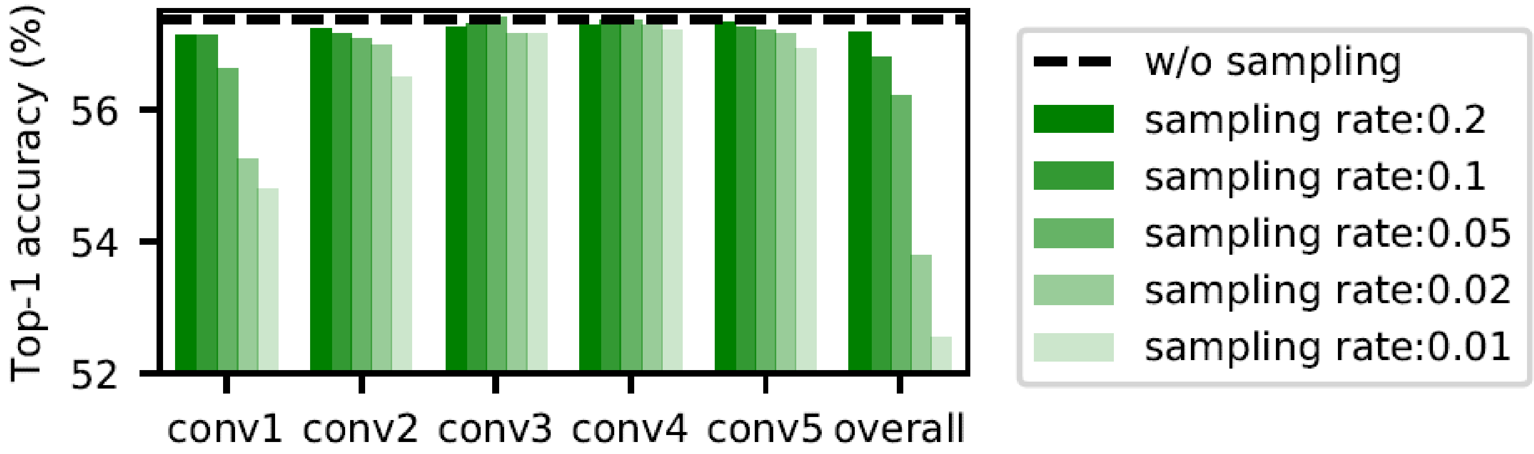
Sampling Rate for Activation Analysis

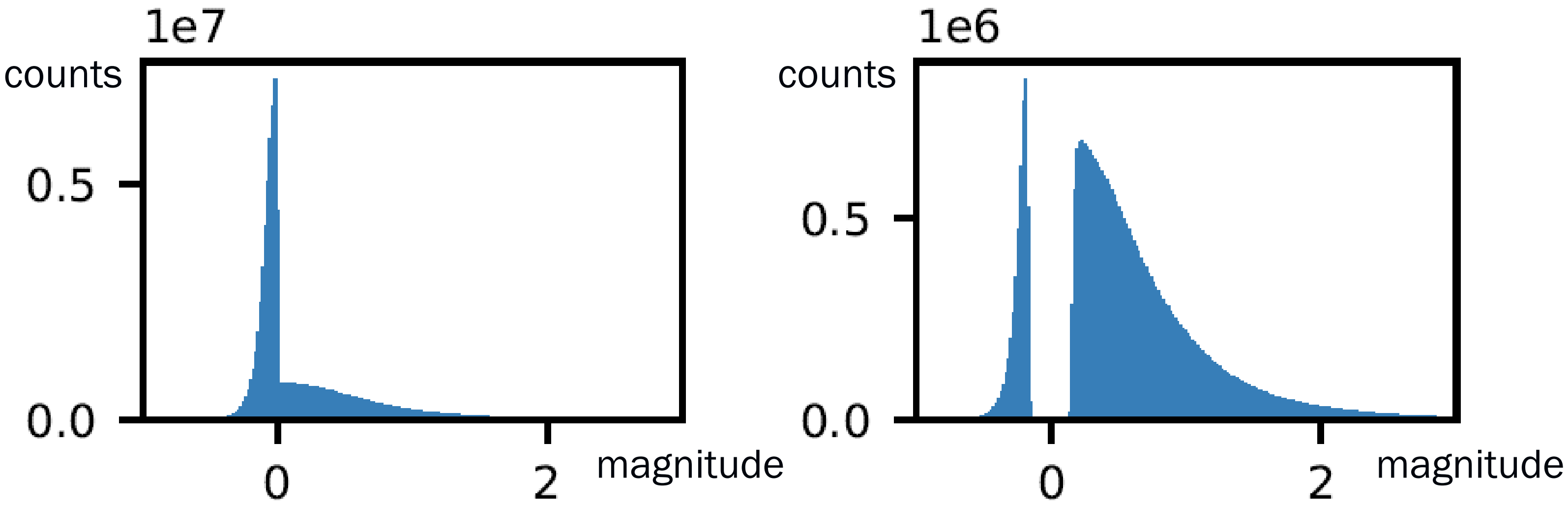
- The identification of activation pruning threshold could be speeded up by predicting on a down sampled activation set
- The effect of sampling on final accuracy is different for layers
- In the AlexNet example, down sampling 10% is a good compromise



The effects of threshold prediction

Activation Distribution

- The activations near zero are pruned out
- The remaining activations have larger magnitude

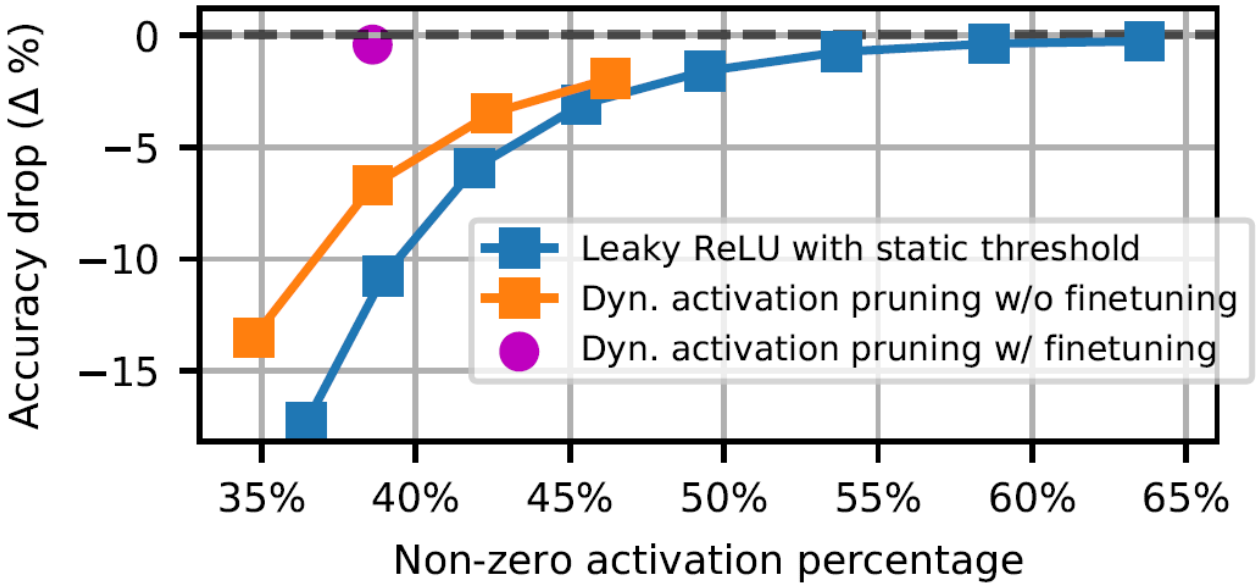


(a) Original. (b) After joint pruning.

Activation distribution of ResNet-32

Compared with Static Activation Pruning

- ResNet-32 with leaky ReLU on CIFAR-10 dataset
- Dynamic activation pruning achieves better performance under the same pruning rate



Comparison to static activation pruning for ResNet-32

Comparison with State of Art Weight Pruning Methods

- Compared with L0, VIB and VD, our method can be easily applied to large models
- Compared with DNS/ADMM, we can obtain minimum prediction error with a comparable computation reduction

COMPARISON WITH THE STATE-OF-THE-ART WEIGHT PRUNING METHODS.

Model	Dataset	Method	Weight %	MAC Reduction	Error
Lenet-4	MNIST	L0	8.9%	5.9×	0.9%
		VIB	0.8%	71.4×	1.0%
		VD	0.4%	80.6×	**0.8%**
		Ours	8.1%	**83.3**×	1.0%
AlexNet*	ImageNet	DNS	32.5%	3.7×	20%
		ADMM	20.5%	**3.8**×	19.8%
		Ours	38.7%	3.7×	**19.6%**

* For AlexNet, we focus on *conv* layers which are the computation bottleneck for inference. The top-5 prediction error is reported in the table.

* Weight % represents percentage of weights after pruning

- **L0**: l_0 regularization
- **VIB**: variational information bottleneck
- **VD**: variational dropout
- **DNS**: dynamic network surgery
- **ADMM**: non-convex problem optimization method

Conclusion

- This work presents a joint regularization algorithm for network pruning, which prunes not only weights but also activations
- Overall, joint regularization outperforms weight only pruning, pointing a promising direction to further network compression
- The model derived from joint regularization requires dedicated DNN accelerators to take the full advantage of the sparsity

Resources

Paper link:

https://arxiv.org/abs/1906.07875

Company website:

http://www.bst.ai/