Cannistraci-Hebb Training of Convolutional NeuralNetworks

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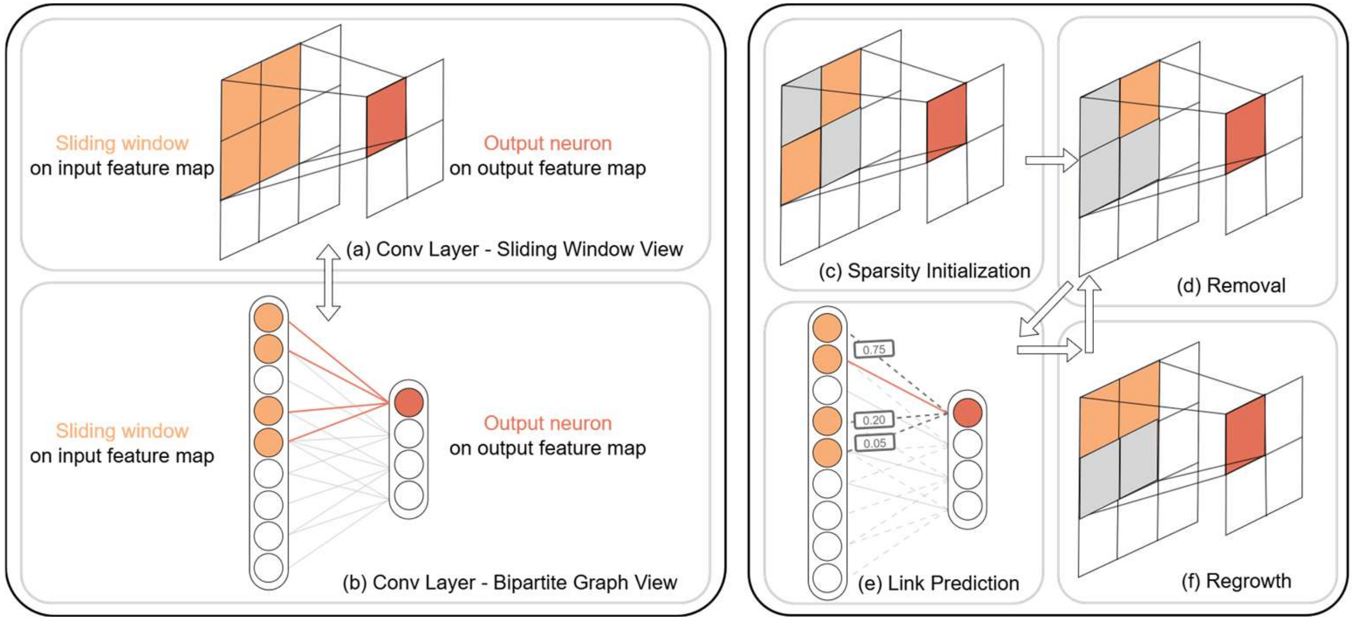
NEURAL INFORMATION PROCESSING SYSTEMS

Introduction

Dynamic sparse training (DST) enables neural networks to evolve their topology during training, which reduces computational overhead while maintaining performance. Cannistraci-Hebb Training (CHT), a brain-inspired method based on epitopological learning principles, has demonstrated significant advantages in building ultra-sparse fully connected networks.

We propose CHT-Conv, extending CHT to convolutional layers while adhering to the inherent constraints of convolutional layers. Experiments on CIFAR-10 and CIFAR-100 using VGG16 architectures show CHT-Conv achieves competitive or superior performance compared to SET baseline at 50\% and 70\% sparsity levels.

$$CH3\_L3(u,v) = \sum_{z_1,z_2 \in L3} \frac{1}{\sqrt{de^*_{z_1} * de^*_{z_2}}}$$



Proposed Method

Initialization, Fig (c)

For each convolutional layer, we initialize a random Boolean tensor mask of the same shape as each kernel to govern which positions are removed at this phase.

Removal, Fig (d)

On each kernel, a fixed fraction positions with the smallest weight magnitudes are removed.

Link Prediction and Regrowth, Fig (e)(f)

With CH link predictors, each inactive positions is assigned a likelihood scores, by which we choose the positions to regrow.

Experimental Results

We evaluate the performance of CHT-Conv on CIFAR10 and CIFAR100 with VGG16.

Preliminary experimental results indicate that:
(1) As sparsity progressively increases, the performance of the network declines;
(2) Compared to SET, the CHT method either outperforms SET (on CIFAR-10) or performs at least comparably to SET (on CIFAR-100).

Sparsity	Method	CIFAR-10	CIFAR-100
0%	Dense	92.14 ± 0.06	$\mathbf{72.58 \pm 0.11}$
50%	SET	92.08 ± 0.10	71.86 ± 0.12
	CHT-CH2	92.04 ± 0.21	72.08 ± 0.06
	CHT-CH3	$\mathbf{92.32 \pm 0.06}$	$\mathbf{72.14 \pm 0.06}$
70%	SET	91.63 ± 0.07	$\mathbf{71.03 \pm 0.13}$
	CHT-CH2	91.73 ± 0.15	70.89 ± 0.23
	CHT-CH3	$\mathbf{92.04 \pm 0.05}$	70.75 ± 0.00

References

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