Deep neural networks are heavily overparameterized models that require significant computational power, which limits its implementation on small devices such as smart phones and robots. Pruning is a popular approach for reducing the computational requirement and facilitating on-device deep learning by setting some weights in the network equal to zero while preserving the performance. In light of the fact that the stochastic gradient descent (SGD) often finds a flat minimum valley in the training loss, we propose a novel directional pruning which searches for a sparse minimizer in the flat region, while the re-training and the expert knowledge to decide the sparsity level are not required. To overcome the computational formidability of estimating the flat directions, we propose to use an l1 proximal gradient algorithm which can provably achieve the directional pruning with small learning rate after sufficient training. The empirical experiments show that our algorithm performs competitively in high sparse regime (92% sparsity) among many existing pruning methods on the ResNet50 with the ImageNet, while using only slightly higher wall time and memory footprint than the SGD. Using the VGG16 and the wide ResNet 28x10 on the CIFAR-10 and CIFAR-100, we show our algorithm reaches the same minima valley as the SGD.

Zoom details can be found at: https://stt.natsci.msu.edu/stt-colloquium-zoom-info/

To request an interpreter or other accommodations for people with disabilities, please call the Department of Statistics and Probability at 517-355-9589.