The role of network geometry in neural architecture design for sparse deep learning

Talk by Carlo Cannistraci

Neural networks models are fundamental tools of modern AI, but the current models adopt a fully connected architecture. Sparse training (ST) aims to ameliorate deep learning by replacing fully connected artificial neural networks (ANNs) with sparse or ultra-sparse ones, such as brain networks are, therefore it might benefit to borrow brain-inspired learning paradigms from complex network intelligence theory.

This talk will introduce CHTs, a brain-inspired network science based training method in sparse deep learning that is gradient free and adopt the mere network topology for predicting the sparse connectivity in dynamic sparse training.

We find in some examples that CHTs can learn ANNs with ultra-sparse (only 1% connectivity) hyperbolic topology in which a community layer organization that is meta-deep (meaning that each layer also has an internal depth due to power-law node hierarchy) develops. The hyperbolic topology is not imposed but emerges naturally during the training process as result of the evolution of the ANNs complex learning dynamics. Furthermore, we discover that CHTs can in many cases automatically sparse the neurons during training.

Empirical results show that CHTs can surpass the performance of fully connected networks with multilayer perceptron architecture by using only 1% of the connections (99% sparsity) on image classification tasks and can even provide remarkable results with only 0.1% of the links (99.9% sparsity). In some cases, CHTs can reduce the active neuron network size to 10% of the original nodes (neurons), demonstrating a remarkable ability to generalize better than fully connected architectures, reducing the entire model size.

Finally, we present evidence from larger network models such as Transformers, with 10% of the connections (90% sparsity), where CHTs outperforms other prevalent dynamic sparse training methods in machine translation tasks.