## TENSORKROWCH: SEAMLESS INTEGRATION OF TENSOR NETWORKS IN MACHINE LEARNING

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Tensor networks, originally stemming from condensed matter physics, are factorizations of high-dimensional tensors into networks of smaller tensors that have found successful applications in physics, mathematics, and more recently, in machine learning.

The pioneering works by Stoudenmire and Schwab [1], and Novikov *et al.* [2] utilizing Matrix Product States (MPS) for supervised learning tasks, opened avenues for employing more complex tensor networks in both supervised and unsupervised learning settings. Recent studies have further explored alternative architectures, including Tree Tensor Networks (TTN) [3, 4] and Projected Entangled Pair States (PEPS) [5]. Furthermore, there is evidence suggesting that tensor networks may even outperform neural networks in certain scenarios [6]. Hybrid models that combine neural network layers with tensor network layers have also been investigated [7].

While there already exist libraries available that are useful for training tensor networks as machine learning models in certain scenarios, there is a distinction among these. Some are highly optimized for (and restricted to) specific tensor network architectures and familiar to machine learning practitioners (e.g., TorchMPS [8]), while others can be used to construct various tensor networks but have a broader focus on physics applications (e.g., TensorNetwork [9]).

To address this disparity, we introduce TensorKrowch [10], a Python library built on top of PyTorch that aims to bring the full power of tensor networks to machine learning practitioners. TensorKrowch empowers users to construct any tensor network model using the familiar language and capabilities of PyTorch. The key strength of TensorKrowch lies in defining a solid set of basic components, namely Nodes and Edges, upon which the entire tensor network can be built. By connecting these Nodes, a complete TensorNetwork model can be created, seamlessly integrating with other PyTorch layers. Consequently, TensorKrowch leverages the full power of PyTorch, including GPU acceleration, automatic differentiation, and easy composition of multi-layer networks. Additionally, TensorKrowch incorporates built-in implementations of widely-used tensor networks such as MPS, TTN and PEPS.

The primary objective of TensorKrowch is to expedite research in the application of tensor networks to machine learning by enabling users to effortlessly create any tensor network while making the training process straightforward. In this talk, I will go through the first steps that newcomers should follow to grasp the basics of TensorKrowch and start training their first custom tensor network model.

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