TedNet: A Pytorch Toolkit for Tensor Decomposition Networks

Yu Pan\textsuperscript{a}, Maolin Wang\textsuperscript{c}, Zenglin Xu\textsuperscript{a,b,*}

\textsuperscript{a}Harbin Institute of Technology Shenzhen, Shenzhen, China
\textsuperscript{b}Pengcheng Lab, Shenzhen, China
\textsuperscript{c}University of Electronic Science and Technology of China, Chengdu, China

Abstract

Tensor Decomposition Networks (TDNs) prevail for their inherent compact architectures. To give more researchers a flexible way to exploit TDNs, we present a Pytorch toolkit named TedNet. TedNet implements 5 kinds of tensor decomposition (i.e., CANDECOMP/PARAFAC (CP), Block-Term Tucker (BTT), Tucker-2, Tensor Train (TT) and Tensor Ring (TR) on traditional deep neural layers, the convolutional layer and the fully-connected layer. By utilizing the basic layers, it is simple to construct a variety of TDNs. TedNet is available at https://github.com/tnbar/tednet.

Keywords: Tensor Decomposition Networks, Deep Neural Networks, Tensor Networks, Network Compression

1. Introduction

Tensor Decomposition Networks (TDNs) are constructed by decomposing deep neural layers with tensor formats. For the reason that the original tensor of a layer can be recovered from tensor decomposition cores, TDNs are often regarded as a compression method for the corresponding networks. Compared with traditional networks like Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), TDNs can be much smaller and occupy a little memory. For example, TT-LSTM 1, BTT-LSTM 2, 3, TR-LSTM 4, 5 are able to reduce 17,554, 17,414 and 34,192 times parameters with a higher accuracy than the original models. With light-weight architectures and good performance, TDNs are promising to be used in kinds of source-restricted scenes including mobile equipment and microcomputers. Due to these advantages, TDNs can often achieve comparably high accuracy with huge parameter reduction in a number of tasks, such as action recognition 6, 7. TDNs have also been implemented in FPGA for fast inference with ultra memory reduction 8 and multi-task learning to improve the representing ability 9. Under this background, we design TedNet package for providing convenience for researchers to explore on TDNs.

There are several related packages, such as T3F 10, Tensorly 11, TensorD 12, TensorNetwork 13, tntorch 14, OSTD 15 and TensorTools 16. OSTD is constructed for low-rank decomposition and implemented with MATLAB. TensorTools based on NumPy 17 implements CP decomposition only, while T3F is explicitly designed for Tensor Train Decomposition on Tensorflow 18. Similarly based on Tensorflow, TensorD supports CP and Tucker decomposition. By contrast, TedNet implements five kinds of tensor decomposition with backend Pytorch 19. TensorNetwork is built on Tensorflow and incorporates abundant tensor calculation tools. Nevertheless, TensorNetwork serves for tensor decomposition algorithms rather than TDNs. Tensorly supports with a variety of backends including CuPy, Pytorch, Tensorflow and MXNet 20. Unfortunately, although Tensorly is powerful to process tensor algebra, tensor decomposition and tensor regressions, it still lacks support to Application Programming Interface (API) to build tensorial neural networks directly. Interestingly, Tensorly can assist to initialize TedNet network modules with its tensor decomposition.
Figure 1: The framework of TedNet. TedNet is based on Pytorch and adopts NumPy to process numerical calculations. Tensor decomposition (TD) can be applied to convolutional layers or linear layers. We implemented 5 variants of tensor decomposition methods, namely CP, Tucker, Tensor Ring, Tensor Train, and Block-term Tucker. Tensor decomposition can be fulfilled in convolution neural networks. An illustration of two tensorial classical neural blocks (i.e., ResNet and LSTM) that are built on the Tensor Decomposition Layer is shown in the right of the figure.

decomposition operation. Compared with them, TedNet can set up a TDN layer quickly by calling API directly. In addition, we also provide three kinds of deep TDNs that are popular for researchers now. Due to the Dynamic Graph Mechanism of Pytorch, TedNet is also flexible to DEBUG for programmers.

2. TedNet Details

TedNet is designed with the goal of building TDNs by calling corresponding APIs, which can extremely simplify the process of constructing TDNs. As shown in Figure 1, TedNet adopts Pytorch as the training framework because of its auto differential function and convenience to build DNN models. In addition, TedNet also uses NumPy [17] to assist in tensor operations. The fundamental module of TedNet is _TNBase, which is an abstracted class and inherits from torch.nn.Module. Thus, TedNet models can be amicably combined with other Pytorch models. As an abstracted class, _TNBase requires sub-classes to implement 4 functions. On the right side of Figure 1, we show two main deep architectures of TedNet, namely TD ResNet and TD LSTM, which are probably the most frequently used backbone in convolutional neural networks and recurrent neural networks, respectively.

Usually, DNNs are constructed with CNNs and Linears. The weight of a CNN is a 4-mode tensor $C \in \mathbb{R}^{K \times K \times C_{in} \times C_{out}}$, where $K$ means the convolutional window, $C_{in}$ denotes the input channel and $C_{out}$ represents the counterpart output channel. And a Linear is a matrix $W \in \mathbb{R}^{I \times O}$, where $I$ and $O$ are length of input and output feature respectively. Similar to DNNs, TDNs consist of TD-CNNs and TD-Linears (For simplification, TD- denotes the corresponding tensor decomposition model), whose weights $C$ and $W$ are factorized with tensor decomposition. Following this pattern, there are 5 frequently-used tensor decomposition (i.e. CP, Tucker-2, Block-Term Tucker, Tensor Train and Tensor Ring) in TedNet, which satisfies most of common situations. Notably, TedNet is an open-source package which supports Tensor Ring

[1] https://github.com/tnbar/tednet/blob/main/tednet/tnn/tn_module.py
Decomposition. Besides, based on TD-CNNs and TD-Linears, TedNet has built some tensor decomposition based Deep Neural Networks, e.g. TD-ResNets, TD-RNNs.

Listing 1: A demo of applying Tensor Ring Decomposition for MNIST Classification.

```python
# Import Tensor Ring Module for Calling
import tednet.tnn.tensor_ring as tr

# Import Necessary Pytorch Modules
import torch
import torch.nn as nn
from torch import Tensor

# A Simple MNIST Classifier based on Tensor Ring.
class TRClassifier(nn.Module):
    def __init__(self):
        super(TRClassifier, self).__init__()

        # Define a Tensor Ring Convolutional Layer
        self.tr_cnn = tr.TRConv2D([1], [4, 5], [6, 6, 6, 6], 3)

        # Define a Tensor Ring Fully-Connected Layer
        self.tr_fc = tr.TRLinear([20, 26, 26], [10], [6, 6, 6, 6])

    def forward(self, inputs: Tensor) -> Tensor:
        # Call TRConv2D to process inputs
        out = self.tr_cnn(inputs)
        out = torch.relu(out)
        out = out.view(inputs.size(0), -1)

        # Call TRLinear to classify the features
        out = self.tr_fc(out)

        return out
```

3. Installation and Illustrative Examples

There are two ways to install TedNet. For the sake that the source code of TedNet is submitted to GitHub, it is feasible to install from the downloaded code by command `python setup.py install`. Compared with aforementioned fussy way, another one, the recommended way is to install TedNet trough PyPI by command `pip install tednet`. After installation, all tensor decomposition models of TedNet can be used.

A simple MNIST classifier based on tensor ring is shown in Listing 1. The tensor ring module can be used by importing `tednet.tnn.tensor_ring`. We utilize two fundamental tensor ring layers (i.e., TRConv2D, TRLinear) to build the sample classifier. In addition, it is very convenient to build a whole tensor ring network with only one line of code, e.g., TR-LeNet5. The usage of other decomposition is the same and more details can be found in the Document.

4. Benchmark

Until now, TDNs are mostly applied in computer vision field. Thus, aiming to validate performance of TedNet, we consider to conduct experiments on two datasets:

- The UCF11 Dataset contains 1,600 video clips of a resolution 320 × 240 and is divided into 11 action categories. Each category consists of 25 groups of videos, within more than 4 clips in one group.

- The Cifar10/100 consists of 50,000 train images and 10,000 test images with size as 32 × 32 × 3. CIFAR10 has 10 object classes and CIFAR100 has 100 categories.

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2https://pypi.org/project/tednet
3https://tednet.readthedocs.io/en/latest/quick_start.html
4https://tednet.readthedocs.io
For the video classification task on UCF11, we adopt the same setting as described in literature [4], where we extract feature of dimension 2048 from each frame of a video by Inception-V3 [22]. Then throw these features as step inputs into TD-LSTMs. Results are shown in Figure 2. Almost every tensor decomposition model can achieve better accuracy except Tucker-2.

For the image classification task on Cifar10/100, we employ ResNet-32 as the backbone network. We show the results of corresponding TD-ResNet-32 implementations with various tensor decomposition in Table 1.

Note that the results shown in Table 1 and Figure 2 are obtained without fine tuning parameters, and are just used for verifying the correctness of these algorithms. Thus the classification results does not mean the performance of these algorithms with the best parameter settings.

5. Conclusion

In this paper, we present a package named TedNet that is specially designed for TDNs. TedNet is completely open-source and distributed under the MIT license. Compared with other related python packages, TedNet contains the most kinds of tensor decomposition.

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| C7  | If available Link to developer documentation/manual  | https://tednet.readthedocs.io/en/latest/index.html                                         |
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Table 2: Code metadata (mandatory)