LibMTL: A Python Library for Multi-Task Learning

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Abstract

This paper presents LibMTL, an open-source Python library built on PyTorch, which provides a unified, comprehensive, reproducible, and extensible implementation framework for Multi-Task Learning (MTL). LibMTL considers different settings and approaches in MTL, and it supports a large number of state-of-the-art MTL methods, including 12 loss weighting strategies, 7 architectures, and 84 combinations of different architectures and loss weighting methods. Moreover, the modular design in LibMTL makes it easy-to-use and well extensible, thus users can easily and fast develop new MTL methods, compare with existing MTL methods fairly, or apply MTL algorithms to real-world applications with the support of LibMTL. The source code and detailed documentations of LibMTL are available at https://github.com/median-research-group/LibMTL and https://libmtl.readthedocs.io, respectively.

Keywords: Multi-Task Learning, Python, PyTorch

1. Introduction

Multi-Task Learning (MTL) (Caruana, 1997; Zhang and Yang, 2021) is an important area in both machine learning community and industrial community. By learning several related tasks simultaneously, this learning paradigm could not only improve the generalization performance but also reduce the storage cost and inference time, thus it has been applied to many real-world scenarios such as automatic driving, natural language understanding, recommendation system, robotic control, bioinformation, and so on (Zhang and Yang, 2021). Although many State-Of-The-Art (SOTA) MTL models have been proposed recently, most of them are implemented in their respective framework with different experimental details or there are no public implementations for them. Therefore, it is not easy to extend existing MTL algorithms to real-world applications or make a fair comparison with them when designing new MTL models.

To remedy such situation, we develop a Python library for MTL called LibMTL, which has three key features. Firstly, LibMTL provides a unified code base to cover different MTL settings such as the single-input and multi-input problems. It allows a convenient, fair, and consistent comparison between different MTL algorithms in various application scenarios. Secondly, built on PyTorch (Paszke et al., 2019), LibMTL has supported lots of SOTA MTL...
models, especially those deep MTL models, including 12 loss weighting strategies, 7 MTL architectures, and different combinations of those two kinds of methods. Thirdly, LibMTL follows the modular design principles, which allows users to flexibly and conveniently add customized components or make personalized modifications. Therefore, users can easily and fast develop new MTL models or apply existing MTL algorithms to new application scenarios with the support of LibMTL.

2. Settings and Approaches in MTL

Suppose there are $T$ tasks and each task $t$ has its corresponding dataset $D_t = \{X_t, Y_t\}$. Let $f(\cdot; \theta, \psi_{1:T})$ denotes an MTL model with task-shared parameters $\theta$ and task-specific parameters $\psi_{1:T}$. MTL aims to train a model $f$ on all datasets $D_{1:T}$ and expects $f$ to perform well on each task. There are usually two settings in MTL: the single-input case where each task has the same input data, i.e., $X_m = X_n$ for any $m \neq n$, and the multi-input case where each task has its own input data, i.e., $X_m \neq X_n$ for any $m \neq n$. Those two settings reply on the application scenarios and they are different in the training implementation.

There are two main lines of research for MTL. The first line is to design the optimization strategy for MTL. Since how to balance multiple training losses in MTL directly affects the update of the task-shared parameters $\theta$, several methods are proposed to balance the losses or gradients of all the tasks in different ways, which are called loss balancing methods and gradient balancing methods, respectively. Lin et al. (2021) have mathematically unified those two types of methods, which are different in implementations, as loss weighting strategies. Besides, gradient balancing methods need to calculate the gradients of the task-shared parameters $\theta$ for every task, which may be computationally intensive when the number of shared parameters or tasks is large. Thus, Sener and Koltun (2018) propose to use gradients of feature representations to approximate the exact gradients of shared parameters, which significantly reduces the computational cost and is followed by other gradient balancing methods such as (Chen et al., 2020; Liu et al., 2021b). Obviously, those two ways to calculate gradients are different in implementations. The second line is to design the architecture in deep neural networks for MTL and it directly determines which parameters are shared and how to share.

Noticeably, those two lines of research are almost orthogonal to each other as the loss weighting methods are mainly related to the objective function while the design of the architecture is to learn relationships between tasks. Thus, loss weighting strategies can be seamlessly combined with architectures to further improve the performance of MTL.

To summarize, as shown in Figure 1, MTL has two settings and its learning approaches can be divided into three categories.
3. The LibMTL Library

In this section, we introduce the LibMTL library, which provides a unified and easy-to-use framework for MTL as mentioned in Section 2. In Section 3.1, we introduce MTL models implemented in LibMTL, which enables consistent and reproducible comparisons between different MTL models. In Section 3.2, we present the modular design in LibMTL, which allows flexible and extensible customization for new MTL methods or potential MTL applications. Finally, we show that LibMTL is more comprehensive and up-to-date than the existing MTL libraries in Section 3.3.

3.1 Supported MTL Methods

Currently, LibMTL supports 12 loss weighting strategies, namely, Equal Weighting (EW), Gradient Normalization (GradNorm) (Chen et al., 2018), Uncertainty Weights (UW) (Kendall et al., 2018), MGDA (Sener and Koltun, 2018), Dynamic Weight Average (DWA) (Liu et al., 2019), Geometric Loss Strategy (GLS) (Chennupati et al., 2019), Projecting Conflicting Gradient (PCGrad) (Yu et al., 2020), Gradient sign Dropout (GradDrop) (Chen et al., 2020), Impartial Multi-Task Learning (IMTL) (Liu et al., 2021b), Gradient Vaccine (GradVac) (Wang et al., 2021), Conflict-Averse Gradient descent (CAGrad) (Liu et al., 2021a), and Random Loss Weighting (RLW) (Lin et al., 2021). Moreover, it supports 7 MTL architectures, i.e., Hard Parameter Sharing (HPS) (Caruana, 1993), Cross-stitch Networks (Misra et al., 2016), Multi-gate Mixture-of-Experts (MMoE) (Ma et al., 2018), Multi-Task Attention Network (MTAN) (Liu et al., 2019), Customized Gate Control (CGC) (Tang et al., 2020), Progressive Layered Extraction (PLE) (Tang et al., 2020), DSelect-k (Hazimeh et al., 2021). Most of the aforementioned methods have no official implementation and are implemented by ourselves. Besides, LibMTL supports combinations of each loss weighting strategy and each architecture, leading to 84 combinations of them in total.

3.2 The Modular Design of LibMTL

Figure 2 shows the overall framework of LibMTL, which is divided into different functional modules to allow users to flexibly and conveniently add customized designs or modifications in any module.

In LibMTL, each module has different functionalities. The Dataloader module is responsible for data pre-processing and loading. The LibMTL.loss module defines loss functions for each task. The LibMTL.metrics module defines evaluation metrics for all the tasks. The above three modules are highly dependent on the MTL problem under investigation. The LibMTL.config module is responsible for all the configuration parameters involved in the training process, such as the corresponding MTL setting (i.e. the multi-input case or not), the potential hyper-parameters of loss weighting strategies and architectures, the training configuration (e.g., the batch size, the running epoch, the random seed, and the learning rate), and so on. This module adopts command-line arguments to enable users to conveniently set those configuration parameters. The LibMTL.Trainer module provides a unified framework for the training process under different MTL settings and for different MTL approaches as introduced in Section 2. The LibMTL.utils module implements some useful
functionalities for the training process such as calculating the total number of parameters in an MTL model. The \texttt{LibMTL.architecture} and \texttt{LibMTL.weighting} modules contain the implementations of various architectures and loss weighting strategies, respectively, as introduced in Section 3.1. The \texttt{LibMTL.model} module includes some popular backbone networks (e.g., ResNet). The last three modules are highly related to MTL models.

Noticeably, such modular design makes \texttt{LibMTL} easy-to-use and well extensible. For example, when applying to new applications, users only need to prepare the new dataloaders and select (or re-define) appropriate loss and metric functions, and they can apply existing MTL methods implemented in \texttt{LibMTL}. Besides, for researchers to develop new MTL methods such as new architectures, they can easily implement their new method with the support of \texttt{LibMTL}, make a fair comparison with existing models, and combine the new architecture with modern loss weighting methods to further improve the performance based on \texttt{LibMTL}.

### 3.3 Comparison to Related Libraries

There are some libraries that have been developed for MTL recently. For example, RMTL (Cao et al., 2019) is implemented in R to support shallow MTL methods such as linear regularized methods. Another library, i.e., MTLV (Rahimi et al., 2021), only provides a few MTL architectures for natural language processing. Compared with them, \texttt{LibMTL} is more comprehensive and up-to-date. Firstly, \texttt{LibMTL} covers more settings and approaches as introduced in Section 2, which means that \texttt{LibMTL} can be applied to more application scenarios. Secondly, \texttt{LibMTL} implements more SOTA MTL models, especially those based on deep neural networks.

### 4. Conclusion

We present \texttt{LibMTL}, a comprehensive and extensible library for MTL. Built on \texttt{PyTorch}, it provides a unified training framework for different settings in MTL and possesses many SOTA MTL algorithms. In our future work, we will continuously maintain this library to incorporate newly proposed MTL models, update the documentations, and add more applications from different areas.
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