MLO Semester Project Proposal – Spring 2019

Understanding some biologically plausible algorithms for model-parallel deep learning training

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1 Introduction

The suitability of the backpropagation of error (BP) algorithm for explaining learning in the brain was questioned soon after it was popularized. For example, it is not biologically plausible and we have several reasons below: (1) it requires symmetric weights; (2) it requires separate phases for inference and learning; (3) the learning signals are not local, but have to be propagated backward, layer-by-layer, from the output units[2].

Many recent work is introduced as a biologically plausible training algorithm and try to address the limitation, e.g., target-propagation (TP) and its variants [LZFB15], feedback-alignment (FA) and its variants [LCTA14, Nøk16, LFG17, Ano19b], as well as some empirical studies over different methods [BSR+18, Ano19a]. Back-propagation with asymmetric weights was also explored in [LLP16].

2 Your Tasks

We would like to

- understand the recent advance of these biologically plausible algorithms,
- examine the performance of these algorithms on MLP and ResNet for CIFAR-10,
- try to improve the training quality,
- (optional) propose new algorithm to match the SOTA performance of DL tasks and efficiently adapt it to model-parallel scenario (e.g., AI chip in the future).

3 Requirements

1. Experience with Machine Learning and Deep Learning,
2. Very familiar with PyTorch,
3. Passionate about the topic.

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[2]This requires that the error derivative has to be transported as a second signal through the network. To transport this signal, the derivative of the non-linearities have to be known.

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