

Semi-Supervised Deep Learning with Memory

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Abstract. We consider the semi-supervised multi-class classification problem of learning from sparse labelled and abundant unlabelled training data. To address this problem, existing semi-supervised deep learning methods often rely on the up-to-date “network-in-training” to formulate the semi-supervised learning objective. This ignores both the discriminative feature representation and the model inference uncertainty revealed by the network in the preceding learning iterations, referred to as the memory of model learning. In this work, we propose a novel Memory-Assisted Deep Neural Network (MA-DNN) capable of exploiting the memory of model learning to enable semi-supervised learning. Specifically, we introduce a memory mechanism into the network training process as an assimilation-accommodation interaction between the network and an external memory module. Experiments demonstrate the advantages of the proposed MA-DNN model over the state-of-the-art semi-supervised deep learning methods on three image classification benchmark datasets: SVHN, CIFAR10, and CIFAR100.

Keywords: Semi-Supervised Learning, Neural Network with Memory.

1 Introduction

Semi-supervised learning (SSL) aims to boost the model performance by utilising the large amount of unlabelled data when only a limited amount of labelled data is available [4, 37]. It is motivated that unlabelled data are available at large scale but labelled data are scarce due to high labelling costs. This learning scheme is useful and beneficial for many applications such as image search [6], web-page classification [2], document retrieval [21], genomics [29], and so forth. In the SSL literature, the most straightforward SSL algorithm is self-training where the target model is incrementally trained by additional self-labelled data given by the model’s own predictions with high confidence [21, 2, 25]. This method is prone to error propagation in model learning due to wrong predictions of high confidence. Other common methods include Transductive SVM [10, 3] and graph-based methods [39, 1], which, however, are likely to suffer from poor scalability to large-scale unlabelled data due to inefficient optimisation.

Recently, neural network based SSL methods [23, 35, 15, 12, 30, 24, 19, 26, 16, 9, 32] start to dominate the progress due to the powerful representation-learning ability of deep neural networks. Most of these methods typically utilise the up-to-date in-training network to formulate the additional unsupervised penalty so

