Dynamic Neural Network for Incremental Learning

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Abstract

Recently, artificial neural networks (ANNs) have been widely applied to machine learning applications. However, they easily suffer from catastrophic forgetting when learning incrementally over tasks. Incremental learning can be divided into data-incremental, class-incremental and the combination of both. The goal of incremental learning is to maintain the performance of previous tasks while learning new tasks.
We present our solution for the data-incremental problem in the openLORIS competition. In this competition, we develop a combined method of knowledge distillation and network expansion. Without using previous data, our method still achieves good performance and low time latency.

1. DNN

Our approach: dynamic neural network (DNN for short) adopts dynamic network expansion for data across dissimilar domains, and knowledge distillation for data in similar domains.

1.1. Network Expansion

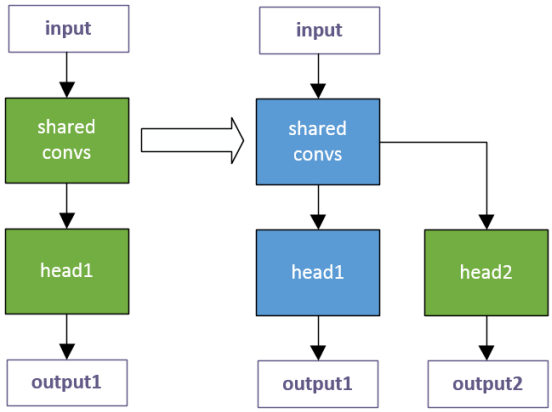

Figure 1. Network expansion.

As shown in Figure 1, we freeze the shared convolutional layers and train new heads for new tasks. We determine the domain gap by measuring the accuracy of the previous model before training on current task.

In order to increase the generalization ability of the trained model, we use ImageNet pre-trained model for the shared convolutional layers, and use more data augmentation and more batches to train head1 for base model.

1.2. Knowledge Distillation

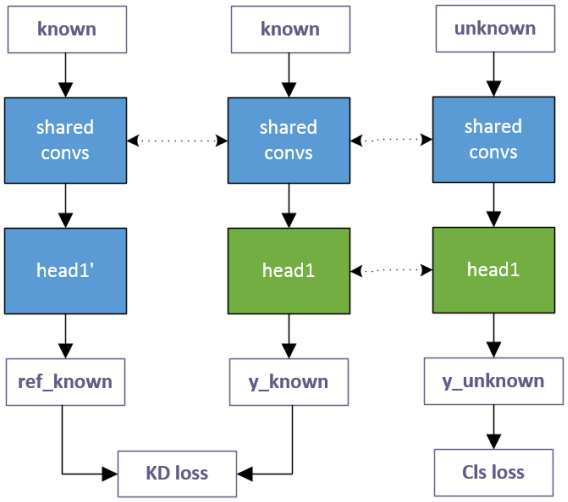

Figure 2. Knowledge distillation.

Without using previous data, we discover known instances in current task by a single forward pass via previous model. Those correctly classified are treated as known samples. We use these samples for knowledge distillation.

To perform knowledge distillation over multiple heads, we must choose a suitable head first. Here, using the best head for distillation is reasonable and more stable verified by experimental results.