Meta-Learning Representation for Continual Learning

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Current intelligent systems based on neural network function approximators are highly prone to forgetting and rarely trained to facilitate future learning. And neural networks are not effective at minimizing the Continual Learning Prediction (CLP) loss using a single trajectory for two reasons. First, they are extremely sample-inefficient, requiring multiple epochs of training to converge to reasonable solutions. Second, they suffer from catastrophic interference when learning online from a correlated stream of data.

To apply neural network to the CLP problem, authors propose meta-learning a function $\phi_\theta(X)$ which is a deep Representation Learning Network (RLN) parametrized by θ. Then a Prediction Learning Network (PLN) g_W is learned. By composing the two functions $f_{W,\theta}(X) = g_W(\phi_\theta(X))$, the model for the CLP tasks is shown in Figure 1. θ is considered as meta-parameters that are learned by minimizing a meta-objective. When θ is learned, g_W for a CLP problem from a single trajectory $\mathcal{S}$ is learned using fully online SGD updates in a single pass.

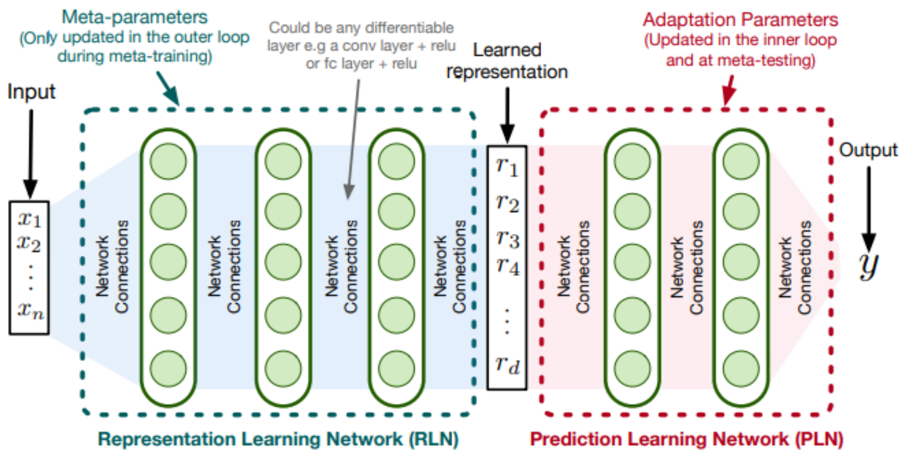

Figure 1: An example of our proposed architecture for learning representations for continual learning. During the inner gradient steps for computing the meta-objective, we only update the parameters in the prediction learning network (PLN). We then update both the representation learning network (RLN) and the prediction learning network (PLN) by taking a gradient step with respect to our meta-objective. The online updates for continual learning also only modify the PLN. Both RLN and PLN can be arbitrary models.

In meta-training, two meta-objectives for updating the meta-parameter θ are considered. MAML-Rep is a MAML like few-shot-learning objective that learns an RLN instead of model initialization. The second one refers to OML (Online aware Meta-learning) that minimizes interference in addition to maximizing fast adaptation for learning the RLN. Therefore, the proposed OML objective is defined as:

$$\min_{W,\theta} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} OML(W,\theta) := \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \sum_{\mathcal{S}_k^j \sim p(\mathcal{S}_k|\mathcal{T}_i)} [\mathcal{L}_{CLP_i}(U(W,\theta,\mathcal{S}_k^j))]$$

where $S_k^j = (X_{j+1}^i Y_{j+1}^i), (X_{j+2}^i Y_{j+2}^i), ..., (X_{j+k}^i Y_{j+k}^i)$. $U(W^t, \theta, S_k^j) = (W_{t+k}, \theta)$ represents an update function where W_{t+k} is the weight vector after k steps of stochastic gradient descent. The jth update step in U is taken using parameters (W_{t+j-1}, θ) on sample $(X_{t+j}^i Y_{t+j}^i)$ to give (W_{t+j}, θ).

The goal of the OML objective is to learn representations suitable for online continual learnings. The optimization of this objective is similar to other gradient-based meta-learning objectives. The successes in the previous works in optimizing similar objectives motivate OML as a feasible objective for Meta-learning Representations for Continual Learning.