Towards a Cortically Inspired Deep Learning Model: 
Semi-Supervised Learning, Divisive Normalization, and Synaptic Pruning

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Abstract

Deep learning has driven dramatic advances in performance on a wide range of difficult machine perception tasks, and its applications abound. Yet for many tasks it still lags far behind the mammalian brain in terms of performance and efficiency in natural tasks. Building a brain-inspired learning system to narrow the gap between artificial and biological neural networks has been a long sought-after goal in both the neuroscience and machine learning communities. To take a step towards a neurally plausible learning system, we build a class of models that use functional elements and computational principles of the cortex for more robust and versatile machine learning. In particular, we incorporate the following three major neural features into the Deep Convolutional Networks (DCNs): semi-supervised learning, divisive normalization, and synaptic pruning. These neural features are derived from a recently developed generative model underlying DCNs - the Deep Rendering Mixture Model (DRMM). Our semi-supervised learning algorithm achieves state-of-the-art performance on the MNIST and SVHN datasets and competitive results on CIFAR10 amongst all methods that do not use data augmentation. Our divisive normalization enables faster and more stable training. Using our synaptic pruning method, we can compress the model significantly with little loss in accuracy. 

Keywords: deep learning; semi-supervised learning; divisive normalization; synaptic pruning

Cortically Inspired Model

Deep Rendering Mixture Model

A fundamental hypothesis of our work is that deep neural networks in the brain are performing probabilistic inference with respect to a generative probabilistic model of the world (Lochmann & Deneve, 2011). But how can we link artificial networks to generative models? The Deep Rendering Mixture Model (DRMM) is a recent effort to reverse-engineer several classes of artificial networks, including the Deep Convolutional Networks (DCNs) (see Figure 1). The DRMM is a hierarchical generative model in which the image is generated iteratively in a coarse-to-fine manner. It has been shown that the bottom-up inference in the DRMM (after a discriminative relaxation), corresponds to the feedforward propagation in the DCNs (Patel, Nguyen, & Baraniuk, 2016). The DRMM allows us to subsume semi-supervised learning, divisive normalization, and synaptic pruning with DCNs in one theoretical framework.

Figure 1: (A) The DRMM (B) Rendering from layer $\ell \rightarrow \ell - 1$ in the DRMM. (C) Bottom-up inference in the DRMM leads to processing identical to the DCNs.

Neural Features for Deep Convolutional Networks

Semi-supervised Learning Current state-of-the-art machine learning algorithms are trained on enormous sets of labeled examples presented in batches to the learning algorithm. In contrast to that, humans and animals learn from few instances of only weakly labeled examples. It is widely believed that the brain is building a rich model for the data in an un- or weakly supervised way such that novel categories can be constructed quickly. We develop a semi-supervised learning algorithm that allows DCNs to learn from both labeled and unlabeled data using the DRMM and variational inference (VI). In particular, our method performs bottom-up and top-down inference in the DRMM and then optimizes the loss function $L \equiv \alpha_{CE} L_{CE} + \alpha_{RC} L_{RC} + \alpha_{KL} L_{KL} + \alpha_{NN} L_{NN}$ where $\alpha_{CE}$, $\alpha_{RC}$, $\alpha_{KL}$ and $\alpha_{NN}$ are the weights for the cross-entropy loss $L_{CE}$, reconstruction loss $L_{RC}$, variational inference loss $L_{KL}$, and the non-negativity penalty loss $L_{NN}$, respectively. The non-negativity penalty loss $L_{NN}$ results from the assumption that the intermediate rendered templates in the DRMM are non-negative.

Divisive Normalization Divisive normalization is a phenomenological model describing the response behavior of...
Table 1: Test error for semi-supervised learning on MNIST with $N_u = 60K$ unlabeled & $N_l \in \{50, 100\}$ labeled images.

<table>
<thead>
<tr>
<th>Model</th>
<th>Test error (%)</th>
<th>$N_l = 50$</th>
<th>$N_l = 100$</th>
</tr>
</thead>
<tbody>
<tr>
<td>calGAN</td>
<td>-</td>
<td>1.39 ± 0.28</td>
<td></td>
</tr>
<tr>
<td>Skip DGM</td>
<td>-</td>
<td>1.32</td>
<td></td>
</tr>
<tr>
<td>LadderNetwork</td>
<td>-</td>
<td>1.06 ± 0.37</td>
<td></td>
</tr>
<tr>
<td>Auxiliary DGM</td>
<td>-</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>ImprovedGAN</td>
<td>2.21 ± 1.36</td>
<td>0.93 ± 0.065</td>
<td></td>
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</tbody>
</table>

DRMM 5-layer Supervised | 22.98
DRMM 5-layer + VI | 2.46 ± 1.35
DRMM 5-layer + VI + $L_{NN}$ | 0.91 | 0.57

Experimental Results

Table 1 shows the test errors of our semi-supervised learning method on MNIST using all available unlabeled data and different amounts of labeled data. Our algorithm can learn more from fewer labeled examples, achieving state-of-the-art performance in semi-supervised learning in different setups on MNIST (see Nguyen, Patel, & Baraniuk, 2017) for results on SVHN and CIFAR10. Note that all methods use the same baseline architecture.

Figure 2 compares the performance of divisive normalization (DN) and batch normalization (BN) on a shape classification task in the semi-supervised learning setup and on an object classification task in an online learning setup. The networks are trained using a synthetic dataset containing 110K rendered images of natural objects with different textures and nuisance configurations. The images are rendered from 1,085 shape models and 55 object models in the ShapeNet library (Chang et al., 2015). Overall, we find that DN converges as fast or faster, and yields more stable learning curves than BN. Importantly, we find that DN has an especially large advantage in the online learning setting. This is because, in contrast to BN, which requires a batch of images to compute a normalization, DN works with a single image and can thus be used in the online setting where one input is processed at a time.

To evaluate our synaptic pruning method, we apply synaptic pruning while training a 9-layer DRMM using our semi-supervised learning algorithm with divisive normalization for object classification task using the synthetic dataset described above. The model is pruned by more than 60% while still achieving good test accuracy (85%).

References


