A GENERATIVE MODEL FOR DEEP CONVOLUTIONAL LEARNING

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ABSTRACT

A generative model is developed for deep (multi-layered) convolutional dictionary learning. A novel probabilistic pooling operation is integrated into the deep model, yielding efficient bottom-up (pretraining) and top-down (refinement) probabilistic learning. Experimental results demonstrate powerful capabilities of the model to learn multi-layer features from images, and excellent classification results are obtained on the MNIST and Caltech 101 datasets.

INTRODUCTION

We develop a deep generative statistical model, which starts at the highest-level features, and maps these through a sequence of layers, until ultimately mapping to the data plane (e.g., an image). The feature at a given layer is mapped via a multinomial distribution to one feature in a block of features at the layer below (and all other features in the block at the next layer are set to zero). This is analogous to the method in Lee et al. (2009), in the sense of imposing that there is at most one non-zero activation within a pooling block. We use bottom-up pretraining, in which initially we sequentially learn parameters of each layer one at a time, from bottom to top, based on the features at the layer below. However, in the refinement phase, all model parameters are learned jointly, top-down. Each consecutive layer in the model is locally conjugate in a statistical sense, so learning model parameters may be readily performed using sampling or variational methods.

MODELING FRAMEWORK

Assume $N$ gray-scale images $\{X^{(n)}\}_{n=1,N}$, with $X^{(n)} \in \mathbb{R}^{N_x \times N_y}$; the images are analyzed jointly to learn the convolutional dictionary $\{D^{(k)}\}_{k=1,K}$. Specifically consider the model

$$X^{(n)} = \sum_{k=1}^{K} D^{(k)} \ast (Z^{(n,k)} \odot W^{(n,k)}) + E^{(n)},$$

(1)

where $\ast$ is the convolution operator, $\odot$ denotes the Hadamard (element-wise) product, the elements of $Z^{(n,k)}$ are in $\{0,1\}$, the elements of $W^{(n,k)}$ are real, and $E^{(n)}$ represents the residual. $Z^{(n,k)}$ indicates which shifted version of $D^{(k)}$ is used to represent $X^{(n)}$.

Assume an $L$-layer model, with layer $L$ the top layer, and layer 1 at the bottom, closest to the data. In the pretraining stage, the output of layer $l$ is the input to layer $l+1$, after pooling. Layer $l \in \{1, \ldots, L\}$ has $K_l$ dictionary elements, and we have:

$$X^{(n,l+1)} = \sum_{k_{l+1}=1}^{K_{l+1}} D^{(k_{l+1},l+1)} \ast (Z^{(n,k_{l+1},l+1)} \odot W^{(n,k_{l+1},l+1)}) + E^{(n,l+1)}$$

(2)

$$X^{(n,l)} = \sum_{k_{l}=1}^{K_{l}} D^{(k_{l},l)} \ast (Z^{(n,k_{l},l)} \odot W^{(n,k_{l},l)}) + E^{(n,l)}$$

(3)

The expression $X^{(n,l+1)}$ may be viewed as a 3D entity, with its $k_{l+1}$-th plane defined by a “pooled” version of $S^{(n,k_{l+1},l)}$.

The 2D activation map $S^{(n,k_{l},l)}$ is partitioned into $n_x \times n_y$ dimensional contiguous blocks (pooling blocks with respect to layer $l + 1$ of the model); see the left part of Figure 1. Associated with each
We here apply our model to the MNIST and Caltech 101 datasets. The learning performed with the top-down generative model (right part of Fig. 1) constitutes a refinement of the parameters learned during pretraining, and the excellent initialization constituted by the parameters learned during pretraining is key to the subsequent model performance.

In the refinement phase, we now proceed top down, from (2) to (3). The generative process constitutes the parameters learned during pretraining, and the excellent initialization constituted by the parameters learned during pretraining is key to the subsequent model performance.

3 EXPERIMENTAL RESULTS

We here apply our model to the MNIST and Caltech 101 datasets.

MNIST Dataset Table 1 summarizes the classification results of our model compared with some related results, on the MNIST data. The second (top) layer features corresponding to the refined dictionary are sent to a nonlinear support vector machine (SVM) (Chang & Lin 2011) with Gaussian kernel, in a one-vs-all setting. The proposed framework enjoys efficient bottom-up and top-down probabilistic inference. A probabilistic pooling module has been integrated into the model, a key component to developing a principled top-down generative model, with efficient learning and inference. Extensive experimental results demonstrate the efficacy of the model to learn multi-layered features from images.
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