Abstract

Convolutional networks have marked their place over the last few years as the best performing model for various visual tasks. They are, however, most suited for supervised learning from large amounts of labeled data. Previous attempts have been made to use unlabeled data to improve model performance by applying unsupervised techniques. These attempts require different architectures and training methods. In this work we present a novel approach for unsupervised training of Convolutional networks that is based on contrasting between spatial regions within images. This criterion can be employed within conventional neural networks and trained using standard techniques such as SGD and back-propagation, thus complementing supervised methods.

1 Introduction

For the past few years convolutional networks (ConvNets, CNNs) have proven themselves as a successful model for vision related tasks. A convolutional network is composed of multiple convolutional and pooling layers, followed by a fully-connected affine transformations. As with other neural network models, each layer is typically followed by a non-linearity transformation such as a rectified-linear unit (ReLU).

A convolutional layer is applied by cross correlating an image with a trainable weight filter. This stems from the assumption of stationarity in natural images, which means that features learned for one local region in an image can be shared for other regions and images.

Deep learning models, including convolutional networks, are usually trained in a supervised manner, requiring large amounts of labeled data (ranging between thousands to millions of examples per-class for classification tasks) in almost all modern applications. These models are optimized a variant of stochastic-gradient-descent (SGD) over batches of images sampled from the whole training dataset and their ground truth-labels. Gradient estimation for each one of the optimized parameters is done by back propagating the objective error from the final layer towards the input. This is commonly known as "backpropagation".

One early well known usage of unsupervised training of deep architectures was as part of a pre-training procedure used for obtaining an effective initial state of the model. The network was later fine-tuned in a supervised manner as displayed by Hinton (2007). Such unsupervised pre-training procedures were later abandoned, since they provided no apparent benefit over other initialization.
heuristics in more careful fully supervised training regimes. This led to the de-facto almost exclusive usage of neural networks in supervised environments.

In this work we will present a novel unsupervised learning criterion for convolutional network based on comparison of features extracted from regions within images. Our experiments indicate that by using this criterion to pre-train networks we can improve their performance and achieve state-of-the-art results.

2 Problems with Current Approaches

The majority of unsupervised optimization criteria currently used are based on variations of reconstruction losses. One limitation of this fact is that a pixel level reconstruction is non-compliant with the idea of a discriminative objective, which is expected to be agnostic to low level information in the input. In addition, it is evident that MSE is not best suited as a measurement to compare images, for example, viewing the possibly large square-error between an image and a single pixel shifted copy of it. Another problem with recent approaches such as [Rasmus et al. 2015, Zeiler et al. 2010] is their need to extensively modify the original convolutional network model. This leads to a gap between unsupervised method and the state-of-the-art, supervised, models for classification - which can hurt future attempt to reconcile them in a unified framework, and also to efficiently leverage unlabeled data with otherwise supervised regimes.

3 Learning by Comparisons

The most common way to train NN is by defining a loss function between the target values and the network output. Learning by comparison approaches the supervised task from a different angle. The main idea is to use distance comparisons between samples to learn useful representations. For example, we consider relative and qualitative examples of the form “X₁ is closer to X₂ than X₁ is to X₃. Using a comparative measure with neural network to learn embedding space was introduced in the “Siamese network” framework by [Bromley et al. 1993] and later used in the works of [Chopra et al. 2005]. One use for this methods is when the number of classes is too large or expected to vary over time, as in the case of face verification, where a face contained in an image has to compared against another image of a face.

4 Our Contribution: Spatial Contrasting

One implicit assumption in convolutional networks, is that features are gradually learned hierarchically, each level in the hierarchy corresponding to a layer in the network. Each spatial location within a layer corresponds to a region in the original image. It is empirically observed that deeper layers tend to contain more ‘abstract’ information from the image. Intuitively, features describing different regions within the same image are likely to be semantically similar (e.g. different parts of an animal), and indeed the corresponding deep representations tend to be similar. Conversely, regions from two probably unrelated images (say, two images chosen at random) tend to be far from each other in the deep representation. This logic is commonly used in modern deep networks such as [Szegedy et al. 2015, Lin et al. 2015, He et al. 2015], where a global average pooling is used to aggregate spatial features in the final layer used for classification.

Our suggestion is that this property, often observed as a side effect of supervised applications, can be used as a desired objective when learning deep representations in an unsupervised task. Later, the resulting representation can be used, as typically done, as a starting point or a supervised learning task. We call this idea which we formalize below Spatial contrasting. The spatial contrasting criterion is similar to noise contrasting estimation [Gutmann and Hyvärinen 2010, Mnih and Kavukcuoglu 2013], in trying to train a model by maximizing the expected probability on desired inputs, while minimizing it on contrasting sampled measurements.

4.1 Formulation

We will concern ourselves with samples of images patches \( \tilde{x}^{(m)} \) taken from an image \( x \). Our convolutional network model, denoted by \( F(x) \), extracts spatial features \( f \) so that \( f^{(m)} = F(\tilde{x}^{(m)}) \).
for an image patch $\tilde{x}^{(m)}$. We wish to optimize our model such that for two features representing patches taken from the same image $\tilde{x}_i^{(1)}, \tilde{x}_i^{(2)} \in x_i$ for which $f_i^{(1)} = F(\tilde{x}_i^{(1)})$ and $f_i^{(2)} = F(\tilde{x}_i^{(2)})$, the conditional probability $P(f_i^{(1)}|f_i^{(2)})$ will be maximized. This means that features from a patch taken from a specific image can effectively predict, under our model, features extracted from other patches in the same image. Conversely, we want our model to minimize $P(f_i|f_j)$ for $i, j$ being two patches taken from distinct images. Following the logic presented before, we will need to sample contrasting patch $\tilde{x}_j^{(1)}$ from a different image $x_j$ such that $P(f_i^{(1)}|f_j^{(2)}) > P(f_i^{(1)}|f_j^{(2)})$, where $f_i^{(1)} = F(\tilde{x}_i^{(1)})$. In order to obtain contrasting samples, we use regions from two random images in the training set. We will use a distance ratio, described earlier ?? for the supervised case, to represent the probability two feature vectors were taken from the same image. The resulting training loss for a pair of images will be defined as

$$L_{SC}(x_1, x_2) = -\log \frac{e^{-\|f_1^{(1)}-f_2^{(2)}\|_2}}{e^{-\|f_1^{(1)}-f_2^{(2)}\|_2} + e^{-\|f_1^{(1)}-f_1^{(2)}\|_2}}$$

Effectively minimizing a log-probability under the SoftMax measure.

### 4.2 Method

Since training convolutional network is done in batches of images, we can use the multiple samples in each batch to train our model. Each image serves as a source for both an anchor and positive patches, for which the corresponding features should be closer, and also a source for contrasting samples for all the other images in that batch. For a batch of $N$ images, two samples from each image are taken, and $N^2$ different distance comparisons are made. The final loss is the average distance ratio for images in the batch:

$$L_{SC}^-\left(\{x_i\}_{i=1}^N\right) = \frac{1}{N} \sum_{i=1}^N L_{SC}(x_i, \{x_j\}_{j\neq i}) = \frac{1}{N} \sum_{i=1}^N \log \frac{e^{-\|f_i^{(1)}-f_i^{(2)}\|_2}}{\sum_{j=1}^N e^{-\|f_i^{(1)}-f_j^{(2)}\|_2}}$$

Since the criterion is differentiable with respect to its inputs, it is fully compliant with standard methods for training convolutional network and specifically using backpropagation and gradient descent. Furthermore, SC can be applied to any layer in the network hierarchy. In fact, SC can be used at multiple layers within the same convolutional network.

### 5 Experiments

In this section we report empirical results showing that using SC loss as an unsupervised pretraining procedure can improve state-of-the-art performance on subsequent classification. In each one of the experiments, we used the spatial contrasting criterion to train the network on the unlabeled images. We then used the trained model as an initialization for a supervised training on the complete labeled dataset.

#### 5.1 Results on STL10

This dataset consists of 100,000 96 × 96 colored, unlabeled images, together with another set of 5,000 labeled training images and 8,000 test images. The label space consists of 10 object classes.

#### 5.2 Results on Cifar10

The well known CIFAR-10 is an image classification benchmark dataset containing 50,000 training images and 10,000 test images. The image sizes 32 × 32 pixels, with color. The classes are airplanes, automobiles, birds, cats, deer, dogs, frogs, horses, ships and trucks. For Cifar10, we used a previously used setting [Coates and Ng 2012] [Hui 2013] [Dosovitskiy et al. 2014] to test a model’s ability to learn from unlabeled images. In this setting, only 4,000 samples from the available 50,000 are used with their label annotation, but the entire dataset is used for unsupervised learning.
Table 1: State of the art results on STL-10 dataset

| Model                                | STL-10 test accuracy |
|--------------------------------------|-----------------------|
| Zero-bias Convnets - Paine et al. [2014] | 70.2%                 |
| Triplet network - Hoffer and Ailon [2015] | 70.7%                 |
| Exemplar Convnets - Dosovitskiy et al. [2014] | 72.8%                 |
| Target Coding - Yang et al. [2015]    | 73.15%                |
| Stacked what-where AE - Zhao et al. [2015] | 74.33%                |
| Spatial contrasting initialization (this work) | 81.34% ± 0.1         |
| The same model without initialization | 72.6% ± 0.1           |

Table 2: State of the art results on Cifar10 dataset with only 4000 labeled samples

| Model                                | Cifar10 (400 per class) test accuracy |
|--------------------------------------|---------------------------------------|
| Convolutional K-means Network - Coates and Ng [2012] | 70.7%                                 |
| View-Invariant K-means - Hui [2013]    | 72.6%                                 |
| DCGAN - Radford et al. [2015]         | 73.8%                                 |
| Exemplar Convnets - Dosovitskiy et al. [2014] | 76.6%                                 |
| Ladder networks - Rasmus et al. [2015] | 79.6%                                 |
| Spatial contrasting initialization (this work) | 79.2% ± 0.3                          |
| The same model without initialization | 72.4% ± 0.1                           |

6 Conclusions and future work

In this work we presented spatial contrasting - a novel unsupervised criterion for training convolutional networks on unlabeled data. Its is based on comparison between spatial features sampled from a number of images. We’ve shown empirically that using spatial contrasting as a pretraining technique to initialize a ConvNet, can improve its performance on a subsequent supervised training. In cases where a lot of unlabeled data is available, such as the STL10 dataset, this translates to state-of-the-art classification accuracy in the final model.

Since the spatial contrasting loss is a differentiable estimation that can be computed within a network in parallel to supervised losses, future work will attempt to embed it as a semi-supervised model. This usage will allow to create models that can leverage both labeled an unlabeled data, and can be compared to similar semi-supervised models such as the ladder network [Rasmus et al. 2015]. It is also apparent that contrasting can occur in dimensions other than the spatial, the most straightforward is the temporal one. This suggests that similar training procedure can be applied on segments of sequences to learn useful representation without explicit supervision.

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