Clustering Learning for Robotic Vision

Eugenio Culurciello, Jordan Bates, Jose Carrasco, Yann LeCun, Clement Farabet

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1 Introduction

In the recent years the fusion of bio-inspired and neuromorphic vision models and machine learning has dominated the development of artificial vision system for the categorization of multiple objects in static frames. Bio-inspired deep networks are computer-vision and computational-neuroscience models of the mammalian visual system implemented in deep neural networks [1–6]. Most deep network architectures are composed of multiple layers (2, 3 typically), where each layer is composed of: linear two-dimensional filtering, non-linearity, pooling of data, output data normalization [8–10]. Recent machine learning research has focused on the task of training such deep networks from the abundant digital data in form of image frames and videos. In particular, deep networks need to learn good feature representations for complex visual tasks such as object categorization and tracking of objects in space and time, identifying object presence and absence. These representation usually involve learning the linear filter weight values from labeled and unlabeled input data. Since labeled data is costly and often ridden with human errors [18, 19], the recent focus is on learning these features purely from unlabeled input data [11, 14–17]. These recent methods typically learn multiple layers of deep networks by training several layers of features, one layer at a time, with varying complexity of leaning models.

Recent techniques based on unsupervised clustering algorithms are especially promising because they use simple learning methods that quickly converge [11]. These algorithms are easy to setup and train and are especially suite for robotics research, because less complex knowledge of machine learning is needed, environment-specific data can be collected quickly with a few minutes of video, setup of custom size deep networks is quick and can be adapted to specific tasks. In addition, real-time operation with efficient networks can be obtained with less than a hour of training and setup, leading

to direct experimentation in robotic experiments. [[[These models are also very interesting to bio-inspired vision research because they provide a close connection between computational neuroscience and machine learning. In particular unsupervised clustering algorithms provide a simplistic model of Hebbian Learning methods, where neurons that respond to the same input are clustered.]]]

In this paper we present results obtained with unsupervised clustering algorithms on the training and operation of deep neural networks for real-time robotic vision systems. We provide simple techniques and open-source software that allows robotic researchers to use deep network in a short setup time and with little or no knowledge of machine learning necessary. The main goal of the paper is not to present state-of-art results on a specific dataset. Rather we use standard published datasets to evaluate the performance of prototype robotic vision system for general-purpose use, where no dataset is available. It is thus not useful to train the network to perform only on one dataset, when the levels of performance would not carry over to another dataset or real-world images. The goal is thus mainly to evaluate the use of unsupervised networks that can support at least ten frames-per-second operation on commercial hardware, such as recent laptop computers.

The paper presents the following key innovations: (1) use of clustering learning for quickly training robotic systems (section 2), (2) the use of distance-based filtering, as opposed to the standard convolution (section 2.2), (3) the experimental proof that clustering learning networks can outperform supervised networks on general purpose robotic tracking tasks (section 4).

2 Methods

In this paper we created and tested a model of unsupervised clustering algorithms (CL) that can quickly learn linear filters weight values, and also is amenable to real-time operation with conventional mobile hardware. We used the Torch7 software for all our experiments [20].

2.1 Input data

Input image data was obtained from the CIFAR10 [21] and the Street View House Numbers (SVHN) [24] datasets. The SVHN dataset has a training size of 73,257 32x32 images and test size of 26,032 32x32 images. the CIFAR10 dataset has training size of 20,000 32x32 images and test size of 2,000 32x32 images.

As testing data for a general-purposed robotic vision system, we decided to test our networks in a tracking task, where the network has to be able to track an object of interest based on a single presentation. For this purpose we use the challenging benchmark TLD dataset [26]. From this dataset we selected multiple videos with different properties of occlusions, camera movement, pose, scale and illumination changes.

Both datasets offer a 10 categories classification task on 32 x 32 size images. The train dataset was in all cases learned to 100% accuracy, and training was then stopped. Input data was contrast normalized separately on each RGB channel with a 9x9 gaussian filter using the Torch7 "nn.Spatial Contrastive Normalization" function.

In terms of color space, we did not convert the input images to YUV, but rather kept them in RGB to keep the model closer to biological human vision, where the retina is broadly sensitive to roughly RGB [25]. Other researchers showed slight improvements using the YUV color space [8].

Also we did not use whitening of data (such as ZCA whitening)even if other groups have shown clear advantages of using it. We did not use whitening because of two main reasons: first it is not applicable for general-purpose vision system where an a-priori dataset cannot be obtained. Second whitening computation is very expensive (similar to the first layer of a convolutional neural network) and we instead replaced it with local contrast normalization, which is a bio-inspired technique to whiten the input data removing its mean bias and adapting the input dynamic range.

2.2 Network architecture

The deep neural network architecture is composed of 4 layers. Two layers of linear two-dimensional filtering and two layers of output classifier in the form of a fully connected 2-layer neural network. The first two layers were composed of a two-dimensional convolutional linear filtering stage, a L2 norm pooling stage, and a subtractive normalization layer for removing the mean of all outputs. The filters of the first two layers are generated with unsupervised clustering algorithms, as explained below. Training of the last two layers fully connected neural network was performed with approximately 300 epochs on the SVHN dataset on a quad-core Intel i7 laptop, or about 8 hours. Test data convergence usually only needed approximately 15 epochs.

The layers in the clustering learning network used the following sequence of operations:

1. SpatialSAD module: performing sum-abs-diff operation on images convolutionally with the learned CL filters

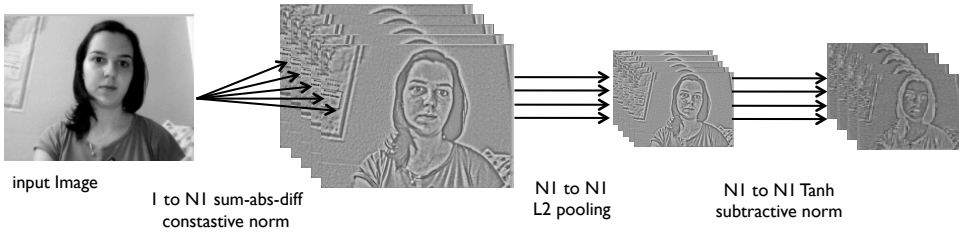


Figure 1: Architecture of one layer of the CL network. Filters were applied with a sum-abs-diff operations, followed by contrastive normalization, L-2 pooling of features, nonlinearity tanh, and subtractive normalization.

2. Spatial Contrastive Normalization: to zero the data mean and standard deviation

3. L2 pooling over 2x2 regions

4. Tanh nonlinearity

5. Spatial Subtractive Normalization: to zero the data mean

In order to show the effectiveness of the learning techniques, we compared them to a standard 1-layer and a 2-layers convolutional neural network (CNN) [7, 9, 10]. The layers in the convolutional neural network used the following sequence of operations:

1. SpatialConvolution module

2. L2 pooling over 2x2 regions

3. Tanh nonlinearity

4. Spatial Subtractive Normalization: to zero the data mean

All networks used 16 filters on the first layer, 128 filters on the second layer. The final classifier was fixed to 128 hidden units and 10 output classes for CIFAR and SVHN. Clustering learning networks used a fully connected input to 1st, and 1st to 2nd layer, while convolutional neural networks used 1-out-of-3 and 4-out-of-16 random connection table between the input and 1st layer, and 1st and 2nd layer respectively.

Notice that CL networks used sum-abs-diff metrics to correlate filters responses to inputs. This is different to the standard approach of deep

networks [1, 8, 16, 21] where convolution operations are used. As will be explained later our choice of sum-abs-diff operations was dictated by improved performance of the CL filters with respect to convolutions. In a standard modern computer the difference between convolutions (multiplications by weights) and distance metrics (differences, subtractions) is not visible, as multipliers are optimized to perform as fast as the simpler difference operations. On the other hand, when programmable hardware as FPGA is used, the use of differences instead of multipliers can reduce the silicon area utilization, and power up to 15 times on a 32 bit operation. A full comparison of the hardware advantages of using distance operators instead of convolutions will be the subject of future publications.

2.3 Learning

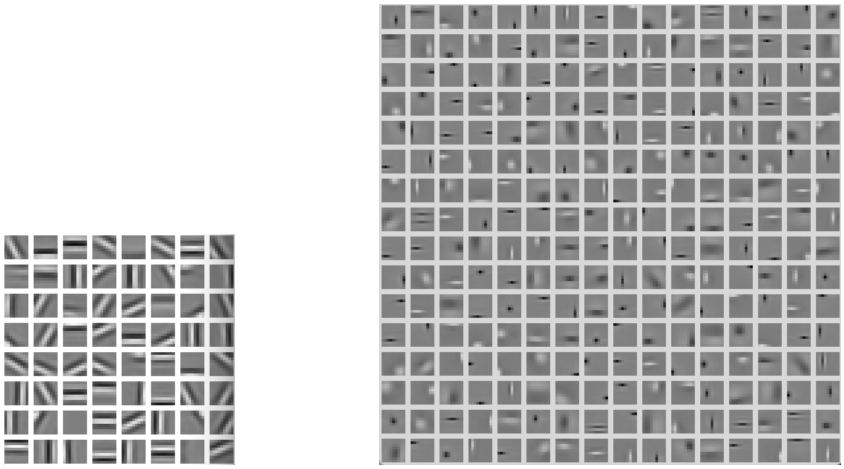
We use k-means clustering algorithm to learn a set of 16 filters in the first layer, and 128 filters in the second layer. The techniques and scripts are general and can quickly modified to learn any number of filters. The filter sizes on both layers was set to 5 x 5 pixels for the SVHN datasets. In CIFAR 1st lair we used 5 x 5 filters, and on the 2nd layer, we used 3 x 3 filters, as features were more spatially constrained in this dataset. Clustering used the same size patches of the normalized images, and we used 1 Million patches from each dataset to train the first layer. The second layer training was performed by passing the entire dataset through the first layer of the deep neural network. The output dataset was then used again with the same script to train another set of linear filters, by using 1 Million patches of the processed dataset.

Clustering learning filters learned on the 2nd layer used as many planes as the 1st layer (16 here). This was done to cluster different sets of features for each output of the 1st layer, and increased performance by an average of 5% or more.

Examples of the filters learned with CL techniques on a 1st and 2nd layer are given in figure 2. Both layer filters were obtained with training for 10 minutes on a modern quad-core Intel i7 laptop. A supervised network of this size would require several tens of thousands of image examples and several hours of training time.

3 Real-time network

The goal of this paper was to provide a simple and fast method to train unsupervised networks for general-purposed robotic vision system. For real-



(a) 1st layer filters (b) 2nd layer filters

Figure 2: Filters obtained with clustering learning on the 1st and 2nd layer. The filters obtained on the 1st layer are quite similar to elongated Gabor patches, and what can be obtained with more complex and numerically involved unsupervised techniques. Filter training with CL was obtained in 10 min time on a modern laptop.

time experiments we used the TLD dataset [26]. We then compared the tracking performance of a real-time deep network both trained supervised [23], and with CL techniques described here.

The CL network for this task had the same two-layer network architecture used in [23]. This insured real-time operation of 6 frames/s on a quad-code Intel i7 laptop computer. We focused on this network and restricted ourselves to real-time operation because the goal of this project is the use of deep networks in mobile computers. The network operates on 46 x 46 input images, uses 16 filters with 7 x 7 receptive field on the first layer and 128 filters with 7 x 7 receptive field on the second layer. The 1st to 2nd layer fan-in was 8, and the 2nd to 3rd layer fan-in was 64. Both layers were connected with random tables. The network produces a 128 feature vector as output.

We trained the same size and number of filters through clustering algorithm for use in this network. We used patches from a contrast normalized version of a few images from the Berkeley image dataset [27]. Any set of natural-scene images can be used to train the general-purpose network presented in this section, and we on purpose chose not to sample patches from

the target TLD dataset, in order to demonstrate the learning invariance properties of our technique.

4 Results

We report the results in the SVHN dataset in figure 3. Here we compared results of accuracy in the test set for 4 cases: clustering learning with 1 layer (CL 1 layer), clustering learning with 2 layers (CL 2 layers), a 1-layer and a 2-layers convolutional neural network (CNN 1l, 2l).

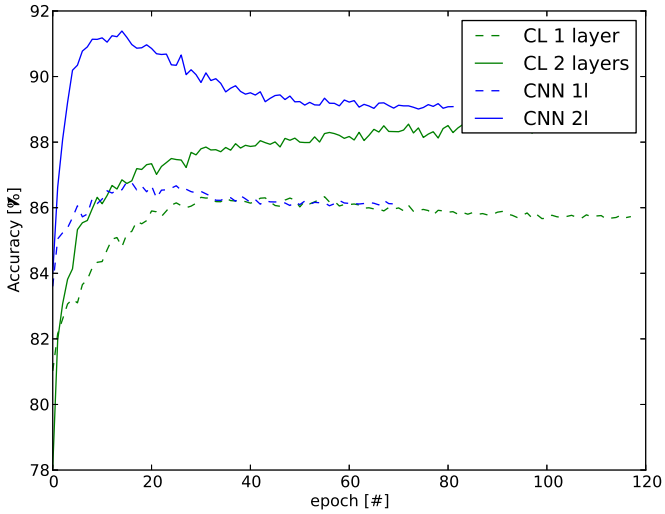


Figure 3: Test set accuracy comparison for a convolutional neural network and a Clustering Learning network with 1 and 2 layers on the SVHN dataset

The data shows that clustering learning and convnet with 1 layer provide remarkably the same levels of accuracy on the dataset. This shows that at least on the 1st layer, the features learned with clustering learning are very effective. Adding a second layer brings the convnet to 91% levels of accuracy, which are standard without using any sophisticated tricks and with a small network with only 16 filters on the first layer. On the other had, the clustering learning network with 2 layers showed more than 2% increase in accuracy, from 86% to 89%. This increase is not as large as one would want and expect from adding a second layer, but is consistent with

unsupervised learning results [11, 12].

It is interesting to note that with in the clustering learning 2 layers network accuracy was above 88%, and plateaued with the train set accuracy plateauing also at 92%. This shows that clustering learning filters also do not over fit, and present non-perfect, but almost identical results on both train and test sets.

The results above were all obtained with feed-forward hierarchical networks. We also tried to use multiple layers of clustering learning unsupervised networks in parallel, as recommended by other publications [9,11], but we did not obtain any benefits from that strategy, on the contrary parallel networks always reported losses of 3-5% accuracy with respect to a single layer.

We also report here the results in the CIFAR10 dataset in figure 4. As in the SVHN case, we compared results of accuracy in the test set for 4 cases: clustering learning with 1 layer (CL 1 layer), clustering learning with 2 layers (CL 2 layers), a 1-layer and a 2-layers convolutional neural network (convnet 1l, 2l).

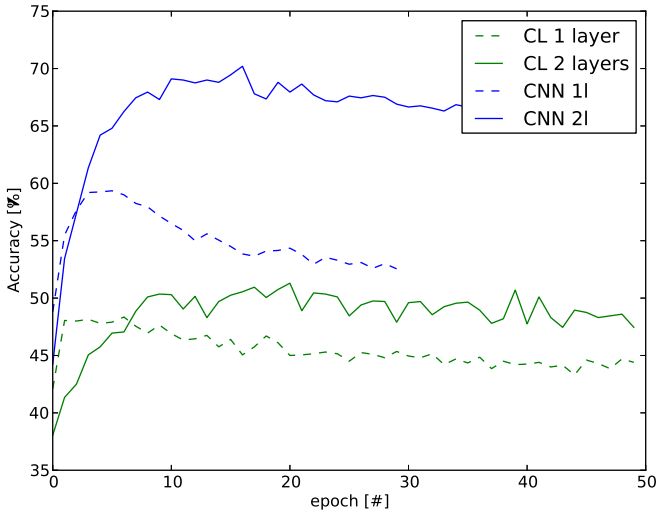


Figure 4: Test set accuracy comparison for a convolutional neural network (CNN) and a Clustering Learning network with 1 and 2 layers on the CIFAR10 dataset

The results in the CIFAR10 dataset show a gain of more than 10% from

using a single layer convnet to a 2 layer convnet. Clustering learning showed the same behavior as in the SVHN dataset: adding a second layer achieved 3-5% better accuracy on the test set. This dataset uses very small images and is notoriously difficult, and clustering learning only reported a 50% accuracy overall with 2 layers. All results are much lower than the current state of art in this dataset, which is close to 90% [30] . But again we stressed our goal was real-time implementation and other researcher have obtained record results in this dataset only with very large networks, most of which are not amenable to real-time operation.

The results for the comparison for the real-time tracking network on the TLD dataset [26] are given in Table 1 Each video contains only one target. The metric used is the number of correctly tracked frames. More information and images on this dataset can be found here [28]. As can be seen in Table 1, the Clustering Learning (CL) network performs better than the convolutional neural network from [23] in all sequences, and is comparable only in one sequence ("Pedestrian 2"). These results are currently not state-of-the-art, which is currently obtained in reference [29].

While the perfomance of the two networks is approximately the same on the TLD dataset, the convolutional neural network from [23] was trained in a week time, while the CL network was tried in 10 minutes. The CL network proved useful for general purpose vision systems

Table 1: Precision comparison between of a Clustering Learning (CL) network and a convolutional neural network (CNN) [23] used as trackers in the TLD dataset [26].

Sequence	Frames	Precision: **CL**	Precision: CNN [23]
David	761	**0.18**	0.08
Jumping	313	**0.37**	0.20
Pedestrian 1	140	**0.81**	0.69
Pedestrian 2	338	0.78	**0.79**
Pedestrian 3	184	**0.45**	0.44
Car	945	**0.67**	0.48
Carchase	9928	**0.38**	0.26

MORE:

x validation: - Cifar net tested in SVHN: 1st epoch: 71- svhn tested on CIFAr: 1st epoch: 40

note: YUV is not bio-inspired: our photo-receptors detect intensity on broad frequencies that are similar to RGB

5 Discussion

I am not sure why people would want to have popularity contests on a single dataset. Since I am after general robot vision I want nets to be trained for any task. So I did a few tests:

trained 2 nets on CIFAR10 and SVHN. Then I tested the one from CIFAR on the SVHN dataset and vice-versa. Results: both give chance performance.

I thought maybe this test is too rough, so I did the same, but kept the output classifier unswitched [meaning I took the one from CIFAR and replaced the output classifier with the SVHN net, then tested on SVHN - also vice-versa] This is equivalent to Results: still both perform at chance

I know these test are unfair because I did not re-train the classifier. So I reloaded the CIFAR convnet first 2 layers and did one epoch on SVHN dataset (also vice-versa) Results: they provide the same kind of results as the 1st epoch of the untrained network.

So I think this demonstrates my point.

Future work: - extension to temporal filters

- Why only 2-4% more with a second layer? and less even with a 3rd? that is a big question

Paper on Convolutional Neural Networks Applied to House Numbers Digit Classification: [7]

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