
Deep and Wide Multiscale Recursive Networks for Robust Image Labeling

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Abstract

Feedforward multilayer networks trained by supervised learning have recently demonstrated state of the art performance on image labeling problems such as boundary prediction and scene parsing. As even very low error rates can limit practical usage of such systems, methods that perform closer to human accuracy remain desirable. In this work, we propose a new type of network with the following properties that address what we hypothesize to be limiting aspects of existing methods: (1) a ‘wide’ structure with thousands of features, (2) a large field of view, (3) recursive iterations that exploit statistical dependencies in label space, and (4) a parallelizable architecture that can be trained in a fraction of the time compared to benchmark multilayer convolutional networks. For the specific image labeling problem of boundary prediction, we also introduce a novel example weighting algorithm that improves segmentation accuracy. Experiments in the challenging domain of connectomic reconstruction of neural circuitry from 3d electron microscopy data show that these “Deep And Wide Multiscale Recursive” (DAWMR) networks lead to new levels of image labeling performance. The highest performing architecture has twelve layers, interwoven supervised and unsupervised stages, and uses an input field of view of 157,464 voxels (54^3) to make a prediction at each image location. We present an associated open source software package that enables the simple and flexible creation of DAWMR networks.

1 Introduction

Image labeling tasks generate a pixel-wise field of predictions across an image space. In boundary prediction, for example, the goal is to predict whether each pixel in an image belongs to the interior or boundary of an object [24]; in scene parsing, the goal is to associate with each pixel a multidimensional vector that denotes the category of object to which that pixel belongs [9]. These types of tasks are distinguished from traditional object recognition, for which pixel-wise assignments are usually irrelevant and the goal is to produce a single global prediction about object identity.

Densely-labeled pixel-wise ground truth data sets have recently been generated for image labeling tasks that were traditionally solved by entirely hand-designed methods [24]. This has enabled the use of learning methods that require extensive supervised parameter learning. As a result, a common class of methods, supervised multilayer neural networks, have recently been found to excel at image labeling and object recognition tasks. This approach has led to state-of-the-art and in some cases breakthrough performance on a diverse array of problems and data sets [9, 19, 12, 3, 15]. Despite these improvements, for most practical applications even higher accuracy is required to achieve reliable automated image analysis. For example, in the main application studied in this paper, reconstruction of neurons from nanometer-resolution electron microscopy images of brain tissue, even small pixel-wise error rates can catastrophically deteriorate the utility of automated analysis [14].

In this paper, we identify limitations in existing multilayer network architectures, propose a novel architecture that addresses these limitations, and then conduct detailed experiments in the domain of connectomic reconstruction of electron microscopy data. The primary contributions of our work are:

1. A ‘wide’ and multiscale core architecture whose labeling accuracy exceeds a standard benchmark of a feedforward multilayer convolutional network. By exploiting parallel computing on both CPU clusters and GPUs, the core architecture can be trained in a day, compared with two weeks for a GPU implementation of the convolutional network.
2. A recursive pipeline consisting of repeated iterations of the core architecture. Through this recursion, the network is able to increase the field of view used to make a prediction at a given image location and exploit statistical structure in label space, resulting in substantial gains in accuracy.
3. A computationally efficient scheme for weighting training set examples in the specific image labeling problem of boundary prediction. This approach, which we refer to as ‘local error density’ (LED) weighting, is used to focus supervised learning on difficult and topologically relevant image locations, and leads to more useful boundary predictions results.

2 Networks for Image Labeling: Prior Work and Desiderata

Multilayer networks for visual processing combine filtering, normalization, pooling, and subsampling operations to extract features from image data. Feature extraction is followed by additional processing layers that perform linear or nonlinear classification to generate the desired prediction variables [17]. Farabet *et al.* recently adapted convolutional networks to natural image scene labeling by training 2d networks that process the image at multiple scales [9]. Boundary prediction in large-scale biological datasets has been investigated using 3d architectures that have five to six layers of processing [13, 33, 12, 32] and, in the work of Ciresan *et al.*, 2d architectures with pooling operations and ensembles of multiple networks [3]. These studies have shown that multilayer networks often outperform alternative machine learning methods, such as MRFs and random forest classifiers. We hypothesize that image labeling accuracy could be further improved by a network architecture that simultaneously addresses all of the following issues:

Narrow vs wide feature representations: The number of features in each layer of a network plays a major role in determining the overall capacity available to represent different aspects of the input space. Most multilayer models for image labeling have thus far been relatively ‘narrow’, *i.e.*, containing a small number of features in each layer. For example, networks described in Jain *et al.* and Farabet *et al.* used respectively 12 and 16 features in the first layer, while those in Ciresan *et al.* used 48. We would like to transition to much wider architectures that utilize thousands of features.

Large field of view: Local ambiguity in an image interpretation task can be caused by noise, clutter, or intrinsic uncertainty regarding the interpretation of some local structures. Global image information can be used to resolve local ambiguity, and thus effective integration of image data over large fields of view is critical to solving an image labeling task. In multilayer visual processing architectures, there are a variety of factors that determine the effective size of the field of view used to compute a prediction for a specific pixel location: filter size, network depth, pooling structure, and multiscale processing pathways. Experiments in this work and others suggest that appropriate usage of all of these architectural components is likely to be necessary to achieve highly accurate image labeling.

While the 2d architecture proposed for scene labeling in Farabet *et al.* is already multiscale, converting the architecture to utilize 3d filters lengthens training time into weeks or more. The 3d boundary prediction networks in Jain *et al.* and Turaga *et al.* have also been augmented with multiscale capabilities, but these modifications lengthen training times from weeks into months.

Modeling and exploiting statistical structure in labels: In the multilayer networks introduced thus far, predictions about neighboring image locations are nearly independent and become potentially correlated only due to a dependence on overlapping parts of the input image. However, in image labeling tasks there is usually a substantial amount of statistical structure among labels at neighboring image locations. This observation suggests that image labeling is a *structured* prediction problem in which statistics among output variables should be explicitly modeled [31]. Markov random field (MRF) image models are an example of a generative approach to structured prediction. These methods consist of an observation model $p(X|Y)$, encoding the conditional distribution of the image X given

the labels \mathbf{Y} , and a prior model $p(\mathbf{Y})$, specifying the distribution over different label configurations. Given a noisy input image X , inference for $p(\mathbf{Y}|X)$ can thus involve both image-dependent aspects (to invert the observation model) as well as interactions among the random variables $Y \in \mathbf{Y}$ that reflect prior statistics on valid label configurations [22].

Multilayer network models for image analysis typically outperform MRFs, as the computational expense associated with probabilistic learning and inference substantially restricts the modeling capability of MRF models that are practical to work with [13, 15]. An alternative approach is pursued by Farabet *et al.*, in which a multilayer network is augmented by a simple three-parameter CRF post-processing step designed to ‘clean up’ classifier predictions. In this work, we propose and investigate a recursive approach in which outputs from one network become input for a subsequent network, thereby allowing for explicit and powerful modeling of statistics among output predictions.

Reasonable training time: We regard it as critical that a network can be learned in a reasonable amount of wall-clock time (within a few days at most, but more ideally within hours). Many existing approaches could conceptually be scaled up to address the limitations that we discuss, but would then require weeks or more in order to train. Such long training times can prohibit certain usage scenarios (for example, interactively adding new labeled data based on rapid classifier retraining [30]). More generally, experimenting in the space of different cost functions, architectures, labeling strategies, *etc.*, is only feasible if a single experiment can be performed in a reasonable duration of time. To achieve a reasonable training time, in this paper we assume access to both graphics processing units (GPUs) and multi-core CPUs or cluster computing environments. Many recent and notable results in machine learning would not have been possible without parallel computing on GPUs or CPUs [19, 4, 28].

3 Deep and Wide Multiscale Recursive Networks

We formalize the image labeling problem as follows: given an input image I , we want to predict at each location $l \in I$ a vector of labels \mathbf{Y}_l . For the main data set considered, I is a three dimensional volume of size on the order of 1000^3 , and with each location is associated a vector of 3 labels ($|\mathbf{Y}_l| = 3$), indicating 3d neighbor connectivity (see Section 4.1.2 for details of the data and labels). For ease of notation we will treat the location l as a single dimension with regard to operations discussed later, such as pooling, but in practice such operations are applied in 3d.

In this section, we describe our proposed method for image labeling, Deep and Wide Multiscale Recursive (DAWMR) networks. DAWMR networks process images by recursive iteration of a core network architecture. Overall, a DAWMR network may have dozens of individual processing layers between the raw input image and final labeling output. A schematic overview of a typical DAWMR network is given in Figure 1.

3.1 Single Iteration Core Architecture

The core network architecture in each iteration consists of two sequential processing modules: feature extraction and classification. These stages are conceptually distinct, learned using differing levels of supervision, and implemented using different parallel computing strategies.

Feature Extraction: Given a location l , the feature extraction module produces h_l , a representation of the input image centered at l . These representations are subsequently passed to the classifier to learn the specific image labeling that is encoded in the training data. (Generally h_l is normalized such that each feature has zero mean and unit standard deviation prior to being passed to the classifier.)

At a high level, each feature extraction module consists of multiple processing layers of feature encoding using vector quantization (VQ), with intermediate layers that apply operations such as pooling, subsampling, and whitening. An entire set of processing layers can be replicated within a single module to process the image at multiple different downsampled scales (where downsampling is achieved by simple averaging). We take advantage of the recent observation that unsupervised clustering and dictionary learning techniques can be used to efficiently learn thousands of features for image recognition tasks [7, 5]. Following Coates and Ng [5], the core vector quantization component in the feature extraction module consists of a dictionary learned using a greedy variant of orthogonal matching pursuit (OMP-1) and encoding using soft-thresholding with reverse polarity.

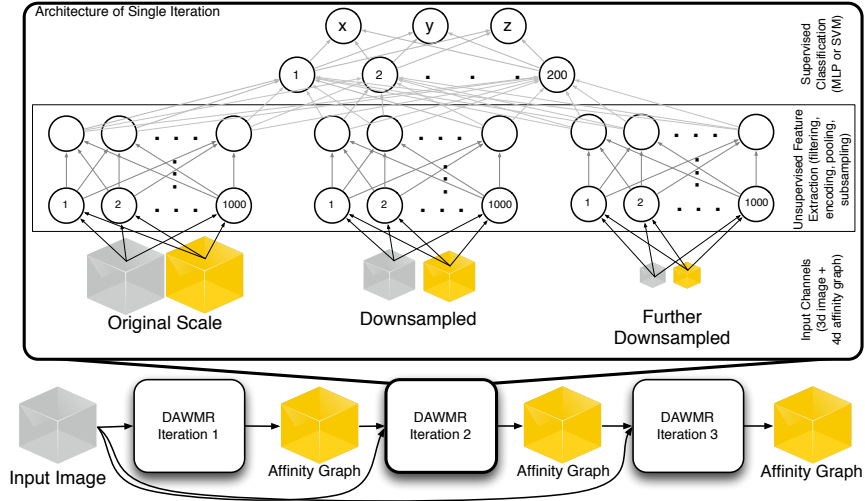


Figure 1: Illustration of a DAWMR network with three recursive iterations.

Given a learned dictionary for performing vector quantization, we can produce an encoding f_i centered at a location i . We consider two contrasting methods for forming a final hidden representation h_l from these encoding f_i . The first method uses the encoding itself as the representation, at various pixel locations centered at i . In what we call an m receptive field (RF) architecture, the hidden representation h_l is formed by concatenating m features, $h_l = \{f_{l-\frac{m}{2}}, \dots, f_{l+\frac{m}{2}}\}$. This is similar to the convolutional network architectures used in [13, 16, 33]; in those networks, classification is based on input from all feature maps in the final hidden layer from feature map values within a 5^3 pixel window centered at the location being classified. The second method is a foveated representation that incorporates pooling operations. Given some neighborhood size m , we first perform max pooling over the neighborhood, $(g_l)_j = \max_{i=l-\frac{m}{2}}^{l+\frac{m}{2}} (h_i)_j$. The foveated representation is then the concatenation of the feature encoding centered at l and the pooled feature, $h_l = \{f_l, g_l\}$. We also experimented with average pooling but found max pooling to give better results in general.

We note that an m RF architecture and a foveated representation with a pooling neighborhood of size m have the same field of view of the data. However, if the dimensionality of the encoding is $|f_i| = k$, then the dimensionality of the hidden representation using an m RF architecture is $|h_l| = mk$, whereas with a foveated representation $|h_l| = 2k$. Therefore, these two methods lie at opposite ends of the spectrum of ‘narrow’ versus ‘wide’ network architectures. Given a fixed hidden representation dimensionality $|h_l| = d$, the m^3 RF architecture will have a narrow VQ dictionary ($\frac{d}{m^3}$) whereas the foveated representation will be able to support a wider VQ dictionary ($\frac{d}{2}$).

Classification: Following the feature extraction module, we have a standard supervised learning problem consisting of features h_l and labels \mathbf{Y}_l . For the classification module, we use a multilayer perceptron (MLP) with a single hidden layer trained by mini-batch stochastic gradient descent [11]. In preliminary experiments, we found that an MLP outperformed a linear SVM. For image labeling problems that involved predicting multiple labels at each location l , we also found that using a single MLP with multiple output units outperformed an architecture with multiple single output MLPs.

Recursive Application of Core Network: In recursive approaches to prediction, a classifier is repeatedly applied to an input (and previous classifier results) to build a structured interpretation of some data. Pioneering work established graph transformer networks for solving segmentation and recognition tasks arising in automated document processing [2]. More recently, recursive approaches have been revived for superpixel agglomeration [29, 16] and text parsing [8].

In image labeling tasks, each pixel in an input image generates a scalar or vector output that encodes predictions about the variables of interest. A straightforward way to directly model statistics *similar* to the labels is to use the output of an initial iteration of the architecture described in Section 3.1 and provide that “network iteration 1” (N_1) output as input to another instance of such an architecture

(N_2). The N_1 output is accompanied by the raw image, and thus feature extraction and subsequent predictions from N_2 are based upon structure in both the original image as well as the output representation from N_1 . Recursive construction of such classifiers is repeated for N_3, \dots, N_k , where k is as large as computation time permits or cross-validation performance justifies.

Each additional recursive iteration also increases the overall field of view used to predict the output at a particular pixel location. Thus, recursive processing enables DAWMR networks to simultaneously model statistical regularities in label-space and use increasing amounts of image context, with the overall goal of refining image labeling predictions from one iteration to the next.

4 Boundary Prediction Experiments

We performed detailed experiments in the domain of boundary prediction in electron microscopy images of neural tissue. This application has significant implications for the feasibility of ‘connectomics’, an emerging endeavour in neurobiology to measure large-scale maps of neural circuitry at the resolution of single-synapse connectivity [23]. Reconstruction is currently the bottleneck in large-scale mapping projects due to the slow rate of purely manual reconstruction techniques [14]. Fully-automated methods for reconstruction would therefore be ideal. Current pipelines typically begin with a boundary prediction step, followed by oversegmentation of the resulting boundary map, and finally application of an agglomeration algorithm to piece together object fragments [1, 16]. Improvements in boundary prediction are desirable, as certain types of errors (such as subtle undersegmentation) can sometimes be difficult to correct during later steps of the reconstruction pipeline.

4.1 Experimental Setup

Here we describe the details of the the image data and training/test sets. Experiments were run using our parallel computing software package, available online¹; for more details see Section C.1.

4.1.1 Image Acquisition

Neuropil from *drosophila melanogaster* was imaged using focused ion-beam scanning electron microscopy (FIB-SEM [18]) at a resolution of $8x8x8$ nm. The tissue was prepared using high-pressure freeze substitution and stained with heavy metals for contrast during electron microscopy. As compared to traditional electron microscopy methods such as serial-section transmission electron microscopy (ssTEM), FIB-SEM provides the ability to image tissue at very high resolution in all three spatial dimensions. Isotropic resolution at the sub-10nm scale is particularly advantageous in *drosophila* due to the small neurite size that is typical throughout the neuropil.

4.1.2 Training, Test Sets

Two image volumes were obtained using the above acquisition process. The first volume was used for training and the second for both validation and testing. Initially, human annotators densely labeled subvolumes from both images. These labels form a preliminary training set, referred to in the sequel as the small training set (5.2 million labels), and the validation set (16 million labels), respectively. Afterward, an interactive procedure was used wherein human annotators ‘proofread’ machine-generated segmentations by visually examining dense reconstructions within small subvolumes and correcting any mistakes. The proofreading interface enabled annotators to make pixel-level modifications. The proofread annotations were then added to the small training set and validation set to form the ‘full’ training set (120 million labels) and test set (46 million labels), respectively.²

The labels are binary and indicate connectivity of adjacent voxels, where positive labels indicate that two voxels belong to the same foreground object and negative labels indicate that two voxels belong to differing objects or both belong to the background. As the image volume is three dimensional, each location is associated with a vector of 3 labels in each direction. The set of such labels (or their inferred probabilistic values) over an image volume is referred to as the affinity graph. By specifying

¹<http://sites.google.com/site/dawmrlib/>

²The validation set is a subset of the test set. Measuring segmentation accuracy requires large densely-labeled subvolumes, and due to the expense in obtaining such data, we believe that measuring final test results on a larger set of data is more valuable for evaluation than splitting off a subset to only be used as validation.

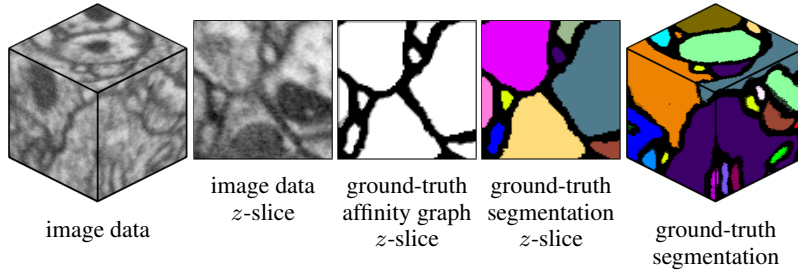


Figure 2: A 79^3 subcube of the test data and z -slice taken from the center of the cube. Shown are the original image data, ground-truth affinity graph, and ground-truth segmentation.

connectivity through an affinity graph it is possible to represent situations (such as directly adjacent, distinct objects) that would be impossible to represent with a more typical pixel-wise exterior/interior labeling [32]. Figure 2 shows a 2d slice of the test image data, affinity graph, and segmentation.

4.1.3 Evaluation Measures

Given a densely-labeled ground truth segmentation, one can measure performance in two ways: classification metrics on binary representations of the segmentation (such as a boundary map or affinity graph), or segmentation-based measures that interpret the volume as a clustering of pixels. In this work, we report both types of measures.

Boundary prediction performance is reported by treating affinity graph edge labeling as a standard binary classification task, where we compute results for each edge direction separately and then average the results over the three edge directions. As the ground truth has a class imbalance skewed toward positive (connected) edges, we report balanced class accuracy (*bal-acc*: $0.5 \cdot \text{accuracy on positive edges} + 0.5 \cdot \text{accuracy on negative edges}$). We also compute area under the receiver operating characteristic curve, when varying the decision threshold for classifying positive/negative edges (*AUC-edge*).

One can also segment a ground truth affinity graph into clusters of connected voxels, forming a set of foreground objects and background. By segmenting an inferred affinity graph (whose labels may be real-valued) at a particular threshold, one can follow the same procedure to form an inferred clustering. We supplement the connected components segmentation by ‘growing out’ segmented objects until they touch each other, using a marker-based watershed algorithm adapted to affinity graphs. Segmentation performance is then measured by computing the Rand Index [34]. We report an area under the curve measure that integrates performance over different binarization thresholds (*AUC-RI*), as well as a maximum score (*max RI*).

4.2 Model Selection Experiments on a Validation Set

Like other deep, multilayer architectures, DAWMR networks have a number of model/architecture parameters that can be varied. In this section, we perform model selection experiments with the validation set. Unless explicitly stated otherwise, our experiments use the following set-up: the feature extraction modules produce a feature representation of dimension $h_l^u = 8000$, individual filters use $3d\ 5^3$ patches, and classification is performed using an MLP with a single hidden layer with 200 hidden units and trained with a balanced sampling of positive and negative training examples.

4.2.1 Single-Iteration Classifiers and Comparison With Convolutional Networks

We begin by evaluating performance of single-iteration DAWMR classifiers and a supervised convolutional network. We consider five DAWMR architectures: 5^3 RF, single-scale vector quantization without pooling (SS), single-scale VQ with foveated representation (SS-FV), and multiscale VQ with foveated representation (MS-FV). We also test a version of the SS-FV architecture with 2d filters (other architectures use 3d filters). For both architectures using a foveated representation, we pool over a 5^3 neighborhood, and thus the 5^3 RF and SS-FV architectures have the same field of view. Table 1 provides an overview of the architectures.

arch.	5^3 RF	SS	SS-FV-2d	SS-FV	MS-FV
VQ dict. size	32	4000	2000	2000	1000
field of view	9^3	5^3	9^2	9^3	18^3
feature dims	8000	8000	8000	8000	8000

Table 1: Vector quantization dictionary size (*i.e.* number of feature maps) and field of view for feature extraction modules in model selection experiments. The multiscale MS-FV architecture uses two dictionaries of size 1000, one for each scale. Table 5 provides details regarding number of free parameters in the network architectures.

Validation performance of single iteration DAWMR networks using the above feature extraction architectures is shown in Table 2. The performance of a supervised convolutional network (CN) is also provided, and represents a strong baseline for comparison; identical types of networks have been extensively used in recent studies involving boundary prediction in 3d electron microscopy data [12, 33, 10]. The CN used in our experiment has 5 hidden layers, 16 feature maps per layer, all-to-all connectivity between hidden layers, and a filter size of 5^3 . The CN was trained on a GPU with an implementation based on the CNS framework [26].

network	training set (small: 5M)			validation set: 16M examples			
	bal-acc	AUC-edge	tr. time	bal-acc	AUC-edge	AUC-RI	max RI
CN	0.9555	0.9872	2 weeks	0.8322	0.8873	0.6692	0.8549
5^3 RF	0.8976	0.9628	1.5 days	0.8200	0.8933	0.6764	0.9194
SS	0.8565	0.9386	1.5 days	0.7946	0.8859	0.6569	0.8757
SS-FV-2d	0.8844	0.9583	1.5 days	0.8024	0.8888	0.6537	0.8496
SS-FV	0.9223	0.9799	1.5 days	0.8129	0.8981	0.6799	0.9049
MS-FV	0.9623	0.9935	1.5 days	0.8305	0.9011	0.6796	0.9086
MS-FV-DO	0.9497	0.9899	1.5 days	0.8372	0.9196	0.7119	0.9327

Table 2: Validation performance of single iteration (non-recursive) DAWMR classifiers for various feature extraction architectures, and comparison with a multilayer convolutional network (CN). SS: single-scale, MS: multiscale, FV: foveated, DO: drop-out. All architectures use 3d filters except SS-FV-2d.

The multiscale foveated architecture (MS-FV) achieves slightly better results than the convolutional network on most metrics, for both the training and test set. The DAWMR classifier is also learned in an order of magnitude less time than the convolutional network. Adding drop-out regularization (MS-FV-DO) improves performance of the single iteration DAWMR classifier even further [11].

4.2.2 Recursive Multiscale Foveated Dropout (MS-FV-DO) Architecture

A specific core architecture can be recursively applied over multiple iterations, as discussed at the end of Section 3.1. In this section we experiment with this approach using the multiscale foveated dropout (MS-FV-DO) architecture. For the second and third iteration classifiers, which accept as input both an affinity graph as well as the original image, there is a model selection choice related to whether filters in the feature extraction stage receive input from only the image, only the affinity graph, or both. We found that dividing the set of features into an equal number which look exclusively at each type of input channel worked better than having all filters receive input from all input channels.

model	iter	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	1	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565
MS-FV-DO	2	0.9447	0.9858	0.8975	0.9551	0.7276	0.9691
MS-FV-DO	3	0.9473	0.9883	0.9024	0.9628	0.7356	0.9691

Table 3: Performance of multiscale foveated architecture over multiple recursive iterations.

Table 3 shows the results from recursive application of the MS-FV-DO architecture. Note that each iteration learns its own unsupervised and supervised parameters, thereby tripling the model parameters used to generate the final output, and that each iteration adds 18^3 to the total field of view used to generate an output prediction by the third iteration classifier (54^3). Recursive experiments were

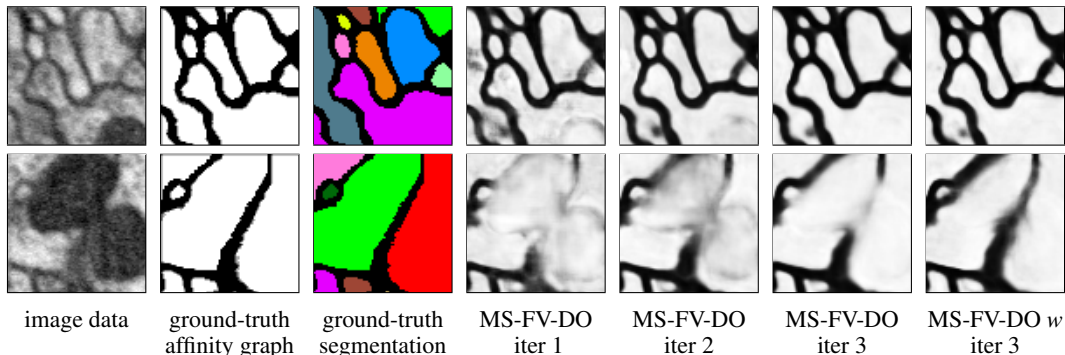


Figure 3: Example image data, ground truth, and DAWMR network output for two different locations from the test set. The second row depicts a difficult situation in which mitochondria from distinct cells are directly adjacent; a recursive DAWMR network trained with LED weighting (MS-FV-DO w iter 3) is able to interpret the data correctly.

limited to three iterations.³ We observe consistent improvements in classification and segmentation metrics as we recursively iterate the core MS-FV-DO architecture.

4.2.3 Recursive MS-FV-DO Architecture with Local Error Density (LED) Weighting

Visual inspection of recursive output confirmed that boundary prediction generally improves over multiple iterations, but also revealed that predictions at certain rare image locations did *not* improve. These locations were characterized by a specific property: a high local density of boundary prediction errors present even in the first iteration output. Locally correlated boundary prediction errors are prone to causing mistakes in segmentation and are thus important to avoid. Yet because these locations are rare, they have a negligible impact on boundary prediction accuracy (the metric actually being optimized during training). Previous work has addressed this issue by proposing learning algorithms that directly optimize segmentation performance [32, 12]. These algorithms are computationally expensive, and can make convergence of online gradient descent sensitive to various parameter choices in the loss function and optimization procedure. Therefore we sought a simpler alternative.

model	iter	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO w	1	0.9336	0.9818	0.8909	0.9502	0.7178	0.9579
MS-FV-DO w	2	0.9453	0.9867	0.8941	0.9524	0.7330	0.9834
MS-FV-DO w	3	0.9536	0.9904	0.9018	0.9606	0.7487	0.9860

Table 4: Performance of multiscale foveated architecture over recursive iterations with LED weighting (w).

Prior to each recursive iteration we train a DAWMR classifier for 20% of the normal number of updates and compute affinity graph output on the training set. We then create a binary weighting mask with non-zero entries for each pixel location in which more than 50% of the affinity edge classifications in a 5^3 neighborhood are incorrect. This simple criteria proves effective in selectively identifying those rare locations where the failure mode occurred. The weighting mask is used during training of the full classifier by sampling weighted locations at a 10x higher rate than normal, and the mask is combined across iterations by ‘or’ing. Table 3 shows results from training a recursive MS-FV-DO architecture with this LED weighting. Weighting increased segmentation accuracy, particularly in the second and third recursive iterations. Boundary prediction classification accuracy was unaffected or even slightly diminished compared to non-weighted results. This is consistent with the idea that weighting alters the cost function to put greater emphasis on specific locations that influence segmentation accuracy, at the expense of overall boundary prediction performance.

³Additional iterations would require a field of view so large that significant amounts of labeled data in the training and validation set would no longer be usable due to insufficient image support.

4.3 Test Set Evaluation and Comparison

Based on the experiments performed on the validation set, we selected a few architectures for evaluation on the full test set. Details of the architectures are reviewed in Table 5, summary results are shown in Table 6, full plots of boundary prediction and segmentation performance are shown in Figure 4, and example 2d slices of the predicted affinity graphs are shown in Figure 3.

model	unsup	sup	fov	training time
CN	0	136000	25 ³	2 weeks
MS-FV-DO	250000	1600803	18 ³	1.5 days
MS-FV-DO <i>w iter 3</i>	750000	4802409	54 ³	5 days

Table 5: Model comparison of architectures chosen from validation set experiments to be evaluated on the test set. |unsup| = number of unsupervised parameters, |sup| = number of supervised parameters, and fov = field of view used to generate boundary predictions for a single image location.

The test set results are consistent with the validation set experiments. Using a 5-million example training set (‘sm’), the MS-FV-DO architecture outperforms the CN with far less training time. Switching to a larger training set (‘lg’) improves MS-FV-DO boundary prediction performance.⁴ Recursive iterations and LED weighting further improves segmentation performance of the DAWMR architecture quite substantially.

model	tr set	training		test set: 46M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
CN	sm	0.9555	0.9872	0.8388	0.8943	0.5927	0.7048
MS-FV-DO	sm	0.9497	0.9899	0.8445	0.9293	0.6798	0.8894
MS-FV-DO	lg	0.9292	0.9809	0.9012	0.9627	0.6939	0.9128
MS-FV-DO <i>w iter 3</i>	lg	0.9536	0.9904	0.9226	0.9735	0.7383	0.9522

Table 6: Performance on the full test set for CN and DAWMR architectures.

The results also confirm previous observations that small differences in boundary prediction accuracy may be associated with large differences in segmentation accuracy [12]. For example, the non-recursive MS-FV-DO architecture outperforms the convolutional network only slightly when measured by *AUC-edge*, but much more substantially under Rand Index metrics. Visual inspection revealed that the convolutional network affinity graphs are more prone to generating undersegmentation errors due to false positive affinity edges between distinct objects.

5 Discussion

Diverse strategies for exploiting image context: The DAWMR networks explored in this work use several different strategies for manipulating the size of the field of view: multiscale processing, pooling, and recursive iteration. It is likely that each strategy offers different modeling capabilities and benefits. For example, multiscale processing is an efficient way to model image features that appear at fundamentally different scales, while recursive processing of the image and affinity graph may be more effective for careful integration of high-frequency features (e.g., contour completion).

In the supplementary, Table 8 shows that a non-recursive architecture that achieves very large field of view in a single iteration performs worse compared to output of a third iteration recursive architecture with a smaller total field of view. As we lack an overall theory for the design of such networks, finding the architecture that makes optimal use of image context requires empirical model selection.

A spectrum of weak vs fine tuning in feature learning schemes: We employ simple unsupervised learning algorithms to learn features in DAWMR networks. These features are likely to be only ‘weakly’ tuned for a specific prediction task, as compared to the ‘finely’ tuned features learned in a convolutional network trained by supervised backpropagation. The trade-off, which our empirical

⁴Technical limitations in our GPU implementation of convolutional networks prevented us from being able to train the CN with the large (lg) training set.

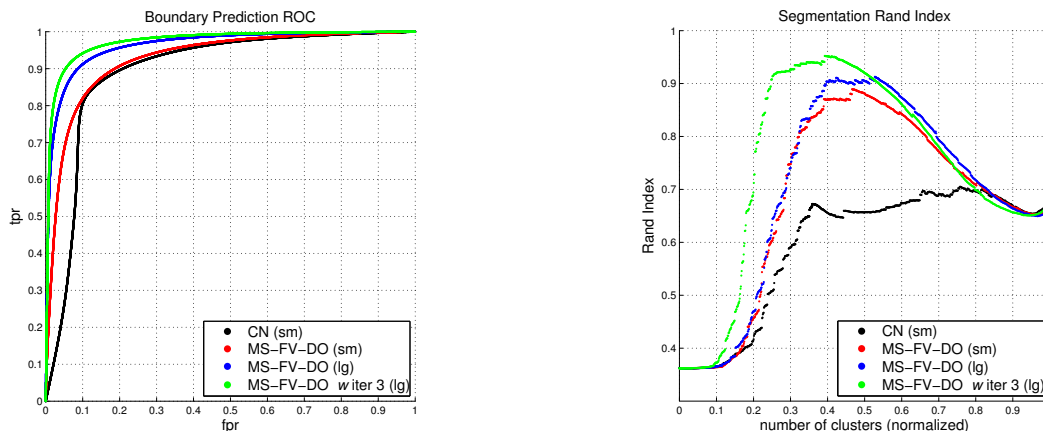


Figure 4: Results on the test set. For Rand Index, x -axis is scaled by the number of clusters in segmentations generated at various binarization thresholds (the specific thresholds are chosen custom to each methods output, in order to yield one-thousand evenly spaced quantiles from the analog affinity graph values).

results suggest are well worth it for the problem of boundary prediction, is in the size of the representation – DAWMR networks can quickly learn thousands of features, whereas for convolutional networks it is currently only practical to use a few dozen at most. Improvements in computing hardware, or fundamentally more parallel versions of stochastic gradient descent may enable larger convolutional network architectures in the future [27, 20].

Recursive iterations and end-to-end learning: In recursive DAWMR networks, each iteration is learned without regard to future iterations. This is in contrast to true ‘end-to-end’ learning, in which each step is optimized based on updates back-propagated from the final output [21, 25]. While end-to-end learning may lead to superior discriminative performance, the cost is twofold: a requirement for using processing stages that are (at least approximately) differentiable, as well as the computational expense of performing a ‘forward’ and ‘backward’ pass through all steps for each parameter update.

We avoid end-to-end learning primarily to minimize training time, but the freedom to use non-differentiable processing steps in conjunction with intermediate affinity graphs presents interesting opportunities. For example, affinity graphs from intermediate iterations could be converted into segmentations from which object-level geometric and morphological features are computed. These features, which may be difficult to represent via differentiable operations such as filtering (e.g., geodesic and histogram-based measures), could be used as additional input to further recursive iterations that refine the affinity graph. This strategy for exploiting object-level representations is an alternative to superpixel-based approaches, and may more easily enable correction of labeling errors that lead to undersegmentation, which is difficult to address in superpixel approaches.

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References

- [1] B. Andres, U. Koethe, T. Kroeger, M. Helmstaedter, K. L. Briggman, W. Denk, and F. A. Hamprecht. 3d segmentation of sbfsem images of neuropil by a graphical model over supervoxel boundaries. *Medical image analysis*, 16(4):796–805, 2012. 4
- [2] L. Bottou, Y. Bengio, and Y. Le Cun. Global training of document processing systems using graph transformer networks. In *Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on*, pages 489–494. IEEE, 1997. 3.1
- [3] D. Ciresan, A. Giusti, J. Schmidhuber, et al. Deep neural networks segment neuronal membranes in electron microscopy images. In *Advances in Neural Information Processing Systems 25*, pages 2852–2860, 2012. 1, 2
- [4] A. Coates, A. Karpathy, and A. Ng. Emergence of object-selective features in unsupervised feature learning. In *Advances in Neural Information Processing Systems 25*, pages 2690–2698, 2012. 2

- [5] A. Coates and A. Ng. The importance of encoding versus training with sparse coding and vector quantization. In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, pages 921–928, 2011. [3.1](#), [A.6](#), [A.7](#)
- [6] A. Coates and A. Ng. Selecting receptive fields in deep networks. In *Advances in Neural Information Processing Systems*, pages 2528–2536, 2011. [A.2](#)
- [7] A. Coates, A. Y. Ng, and H. Lee. An analysis of single-layer networks in unsupervised feature learning. In *International Conference on Artificial Intelligence and Statistics*, pages 215–223, 2011. [3.1](#)
- [8] R. Collobert. Deep learning for efficient discriminative parsing. In *International Conference on Artificial Intelligence and Statistics*, pages 224–232, 2011. [3.1](#)
- [9] C. Farabet, C. Couprie, L. Najman, and Y. LeCun. Scene parsing with multiscale feature learning, purity trees, and optimal covers. *arXiv preprint arXiv:1202.2160*, 2012. [1](#), [2](#)
- [10] M. Helmstaedter, K. L. Briggman, S. C. Turaga, V. Jain, H. S. Seung, and W. Denk. Connectomic reconstruction of the inner plexiform layer in the mouse retina. *Nature*, 500(7461):168–174, 2013. [4.2.1](#)
- [11] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. *arXiv preprint arXiv:1207.0580*, 2012. [3.1](#), [4.2.1](#)
- [12] V. Jain, B. Bollmann, M. Richardson, D. Berger, M. Helmstaedter, K. Briggman, W. Denk, J. Bowden, J. Mendenhall, W. Abraham, K. Harris, N. Kasthuri, K. Hayworth, R. Schalek, J. Tapia, J. Lichtman, and H. Seung. Boundary Learning by Optimization with Topological Constraints. In *Computer Vision and Pattern Recognition, IEEE Computer Society Conference on*, 2010. [1](#), [2](#), [4.2.1](#), [4.2.3](#), [4.3](#), [B.1](#)
- [13] V. Jain, J. F. Murray, F. Roth, S. C. Turaga, V. Zhigulin, K. L. Briggman, M. N. Helmstaedter, W. Denk, and H. S. Seung. Supervised learning of image restoration with convolutional networks. *Computer Vision, IEEE International Conference on*, 0:1–8, 2007. [2](#), [3.1](#), [B.1](#)
- [14] V. Jain, H. Seung, and S. Turaga. Machines that learn to segment images: a crucial technology for connectomics. *Current opinion in neurobiology*, 2010. [1](#), [4](#)
- [15] V. Jain and S. Seung. Natural image denoising with convolutional networks. In *Advances in Neural Information Processing Systems*, pages 769–776, 2008. [1](#), [2](#)
- [16] V. Jain, S. C. Turaga, K. Briggman, M. N. Helmstaedter, W. Denk, and H. S. Seung. Learning to agglomerate superpixel hierarchies. In *Advances in Neural Information Processing Systems*, pages 648–656, 2011. [3.1](#), [4](#)
- [17] K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun. What is the best multi-stage architecture for object recognition? In *Computer Vision, 2009 IEEE 12th International Conference on*, pages 2146–2153. IEEE, 2009. [2](#)
- [18] G. Knott, H. Marchman, D. Wall, and B. Lich. Serial section scanning electron microscopy of adult brain tissue using focused ion beam milling. *Journal of Neuroscience*, 28(12):2959, 2008. [4.1.1](#)
- [19] A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems 25*, pages 1106–1114, 2012. [1](#), [2](#)
- [20] Q. V. Le, M. Ranzato, R. Monga, M. Devin, K. Chen, G. S. Corrado, J. Dean, and A. Y. Ng. Building high-level features using large scale unsupervised learning. *arXiv preprint arXiv:1112.6209*, 2011. [5](#)
- [21] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998. [5](#)
- [22] S. Li. *Markov random field models in computer vision*. Springer, 1994. [2](#)
- [23] J. W. Lichtman and W. Denk. The big and the small: challenges of imaging the brain’s circuits. *Science*, 334(6056):618–623, 2011. [4](#)
- [24] D. R. Martin, C. C. Fowlkes, and J. Malik. Learning to detect natural image boundaries using local brightness, color, and texture cues. *IEEE Trans. Patt. Anal. Mach. Intell.*, pages 530–549, 2004. [1](#)
- [25] U. Muller, J. Ben, E. Cosatto, B. Flepp, and Y. L. Cun. Off-road obstacle avoidance through end-to-end learning. In *Advances in neural information processing systems*, pages 739–746, 2005. [5](#)
- [26] J. Mutch, U. Knoblich, and T. Poggio. CNS: a GPU-based framework for simulating cortically-organized networks. Technical report, Massachusetts Institute of Technology, 2010. [4.2.1](#)
- [27] F. Niu, B. Recht, C. Ré, and S. J. Wright. Hogwild!: A lock-free approach to parallelizing stochastic gradient descent. *arXiv preprint arXiv:1106.5730*, 2011. [5](#)
- [28] N. Pinto, D. Doukhan, J. J. DiCarlo, and D. D. Cox. A high-throughput screening approach to discovering good forms of biologically inspired visual representation. *PLoS computational biology*, 5(11):e1000579, 2009. [2](#)
- [29] R. Socher, C. C. Lin, A. Ng, and C. Manning. Parsing natural scenes and natural language with recursive neural networks. In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, pages 129–136, 2011. [3.1](#)
- [30] C. Sommer, C. Straehle, U. Kothe, and F. A. Hamprecht. Ilastik: Interactive learning and segmentation toolkit. In *Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on*, pages 230–233. IEEE, 2011. [2](#)
- [31] I. Tsochantaridis, T. Joachims, T. Hofmann, and Y. Altun. Large margin methods for structured and interdependent output variables. In *Journal of Machine Learning Research*, pages 1453–1484, 2005. [2](#)

- [32] S. C. Turaga, K. L. Briggman, M. Helmstaedter, W. Denk, and H. S. Seung. Maximin affinity learning of image segmentation. In *NIPS*, 2009. 2, 4.1.2, 4.2.3
- [33] S. C. Turaga, J. F. Murray, V. Jain, F. Roth, M. Helmstaedter, K. Briggman, W. Denk, and H. S. Seung. Convolutional networks can learn to generate affinity graphs for image segmentation. *Neural Computation*, 22(2):511–538, 2010. 2, 3.1, 4.2.1, B.1
- [34] R. Unnikrishnan, C. Pantofaru, and M. Hebert. Toward objective evaluation of image segmentation algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(6):929, 2007. 4.1.3

A Supplementary: Additional Model Selection

We report the results of additional model selection experiments for architectures and learning parameters that were less central to achieving the highest performance in the main presentation.

A.1 Effect of Training Set Size

As noted in Section 4.1.2, two training sets were produced, a small training set (5.2M examples) and a full training set (120M examples), in order to examine how training set size affects DAWMR classification performance.

We augment the full training set by transforming the original data to create synthetic training examples. Specifically, we apply rotations and reflections to the original image data and labels, using a total of seven additional transformations to augment the full training set by a factor of eight. Given the large size of the augmented full training set ($120M * 8$), we also subsample examples within each densely labeled subvolume in order to reduce computational load. Training examples that are nearby spatially are likely to have similar statistics, and thus we found that we can achieve comparable performance while using only a subset (10%) of the full training data.⁵

The augmented, subsampled version of the full training data constitutes the ‘large’ (lg) training set referenced in further experiments. Performance while varying the training set is shown in Table 7.

model	training			validation set: 16M examples			
	tr set	bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
SS-FV-DO	sm	0.9139	0.9737	0.8383	0.9175	0.6989	0.9411
SS-FV-DO	lg	0.9092	0.9721	0.8667	0.9386	0.6907	0.9311
MS-FV-DO	sm	0.9497	0.9899	0.8372	0.9196	0.7119	0.9327
MS-FV-DO	lg	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565

Table 7: Performance of single iteration DAWMR classifiers when varying the size of the training set.

Expanding the training set results in a significant increase in boundary prediction classification accuracy, but has a somewhat ambiguous impact on segmentation performance. These results suggest that, as training sets become large, improvements in segmentation accuracy may require additional model capacity or learning algorithms more explicitly focused on segmentation performance. We investigate both of these issues in subsequent experiments.

A.2 Deeper Feature Extraction Stage

In the DAWMR architectures discussed in the main text, the unsupervised stage had a layer of filtering, followed by encoding and pooling. We experimented with adding a second set of filtering, encoding, and pooling steps. This modification adds the ability to learn higher-order image features from the data, and also dramatically increases the field of view of a single iteration architecture. We used a pairwise-similarity scheme to group first layer filters [6].

model	fov	training set (large)		40% of validation set			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	18 ³	0.9292	0.9809	0.8831	0.9496	0.7186	0.9464
MS-FV-DO iter 3	54 ³	0.9473	0.9883	0.9021	0.9628	0.7371	0.9633
MS-FV-DO-DFE	62 ³	0.9373	0.9851	0.8876	0.9539	0.7263	0.9627

Table 8: Performance of DAWMR architectures from the main text compared to an architecture with a deeper feature extraction stage (MS-FV-DO-DFE). Validation numbers are on a subset of the validation set and thus *not* comparable to numbers in the main text (a subset was used due to clipping effects caused by the large field of view of the MS-FV-DO-DFE architecture).

⁵The training data consists of many densely labeled subvolumes; using only 10% of the subvolumes would lead to a much different and less informative training set as compared to the subsampling scheme we propose – using *all* labeled subvolumes and randomly sampling 10% of the examples within each.

We find that this deeper single-iteration architecture, MS-FV-DO-DFE, improves performance over the standard architecture (MS-FV-DO). However, performance of the recursive architecture is superior, even while using less image context, suggesting that immediately jumping to a large field of view based on deeper unsupervised feature extraction is not necessarily ideal. We also note that inference in the MS-FV-DO-DFE architecture is significantly more computationally expensive than the MS-FV-DO architecture, due to the much larger number of filtering computations in the feature extraction stage.

A.3 Varying Feature Dimensionality

We experimented with varying the dimensionality of the feature representation produced by the unsupervised feature extraction stage of the DAWMR networks, by varying the size of the dictionary used for vector quantization. The results, shown in Table 9, confirm our general hypothesis that wider networks produced by using a large dictionary yield increased performance.

model	dim.	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	400	0.9103	0.9727	0.8710	0.9405	0.6995	0.9236
MS-FV-DO	800	0.9176	0.9749	0.8760	0.9466	0.7078	0.9444
MS-FV-DO	2000	0.9247	0.9775	0.8810	0.9467	0.7027	0.9533
MS-FV-DO	4000	0.9270	0.9793	0.8828	0.9468	0.7136	0.9452
MS-FV-DO	8000	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565
MS-FV-DO	12000	0.9301	0.9803	0.8878	0.9495	0.7144	0.9375

Table 9: Performance of DAWMR architectures when varying the dimensionality of the feature representation from the unsupervised stage.

A.4 Varying the Number of MLP Hidden Units

We also experimented with varying the number of hidden units used in the supervised MLP classifier, with results shown in Table 10. All classifiers were trained using the same fixed number of updates. In general we found the results to not be especially sensitive to this parameter, and used 200 as a balance between sufficient capacity and faster training and convergence.

model	# h.u.	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	50	0.9225	0.9770	0.8793	0.9467	0.7197	0.9444
MS-FV-DO	100	0.9279	0.9795	0.8849	0.9491	0.7063	0.9532
MS-FV-DO	200	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565
MS-FV-DO	400	0.9278	0.9762	0.8833	0.9438	0.7027	0.9272

Table 10: Performance of DAWMR architectures when varying the number of hidden units (h.u.) used in supervised MLP.

A.5 Varying the Number of MLP Hidden Layers

We experimented with adding additional layers of hidden units in the supervised MLP classifier, with results shown in Table 11. The network was kept at a fixed width of 200 hidden units at each hidden layer, and a drop-out rate of 0.5 was used at each hidden layer. All classifiers were trained using the same fixed number of updates.

A.6 Whitening

Previous work with vector quantization and deep learning architectures has noted the importance of whitening the data prior to dictionary learning [5]. We experimented with adding contrast normalization and ZCA whitening to the DAWMR networks. As shown in Table 12, we generally found that both contrast normalization and whitening generally decreased performance slightly. These results seem to indicate the importance of keeping information about intensity values relative to the

model	# h.l.	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	1	0.9330	0.9820	0.8890	0.9521	0.7206	0.9519
MS-FV-DO	2	0.9363	0.9848	0.8910	0.9560	0.7308	0.9547
MS-FV-DO	3	0.9396	0.9851	0.8945	0.9594	0.7393	0.9586
MS-FV-DO	4	0.9323	0.9829	0.8888	0.9563	0.7311	0.9476

Table 11: Performance of DAWMR architectures when varying the number of hidden layers (h.l.) used in supervised MLP.

global data rather than just a local patch, for this particular data set and in distinction to other data such as natural images.

For DAWMR networks with multiple feature encoding steps, as presented in Section A.2, we have had success with combining a small number of features produced by a single VQ step and no whitening with a larger number of features produced by multiple VQ steps and whitening.

model	training set (large)		validation set: 16M examples			
	bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO + CN,WH	0.9191	0.9746	0.8722	0.9411	0.7039	0.9142
MS-FV-DO	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565

Table 12: Performance of DAWMR architecture when adding contrast normalization (CN) and ZCA whitening (WH).

A.7 Orthogonal Matching Pursuit vs K-means

In initial experiments, we used K-means for dictionary learning and “triangle K-means” for feature encoding [5]. This is compared with the Orthogonal Matching Pursuit that we used in the main presentation in Table 13. In general, we found both to give comparable results, with OMP allowing for faster feature encoding and seeming to be more amenable to multiple layers of feature encoding (Section A.2).

model	learning	training set (large)		validation set: 16M examples			
		bal-acc	AUC-edge	bal-acc	AUC-edge	AUC-RI	max RI
MS-FV-DO	K-means	0.9317	0.9819	0.8852	0.9499	0.7195	0.9321
MS-FV-DO	OMP	0.9292	0.9809	0.8833	0.9497	0.7171	0.9565

Table 13: Performance of DAWMR architectures when varying the unsupervised stage dictionary learning method and feature encoding.

B Supplementary: Network Details

Here we present details and values of parameters used in our models.

B.1 Convolutional Network

The convolutional network was trained in accordance with procedures outlined in previous work [13, 33]. We used sigmoid units and performed greedy layer-wise training of the architecture: 5e5 updates after adding each layer, 2e6 updates for the final architecture. Networks trained with significantly fewer iterations exhibited much worse training set performance. During training, we used a balanced sampling strategy that alternated between negative and positive edge locations and selected a 5³ cube around each edge as a minibatch. Learning rates were set to 0.1, except for the last layer (set to 0.01). A square-square loss [33, 12] was optimized with a margin of 0.3.

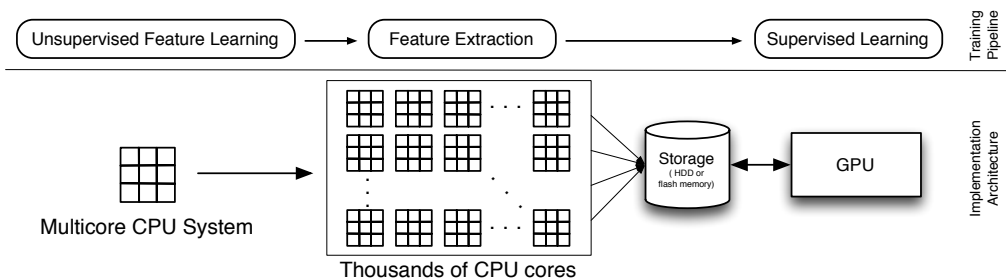


Figure 5: Computation architecture used in experiments. A CPU cluster is used to pre-compute feature vectors prior to GPU-based training of a supervised classifier.

B.2 Multilayer Perceptron

The multilayer perceptrons in DAWMR architectures were trained using minibatch sizes of 40 with a balanced sampling of positive and negative edges. Learning rates were set to 0.02. We used sigmoid output units and rectified linear units in the hidden layer. For networks trained with drop-out regularization, the drop-out rate was set to 0.5 for the hidden layer and 0 for the input layer. We performed $5e5$ updates. Optimization was performing using a cross-entropy loss function. To regularize and prevent overfitting, we used an “inverse margin” of 0.1, meaning that target labels were set to 0.1/0.9 rather than 0/1, penalizing over-confident predictions.

C Supplementary: DAWMR Implementation and Training Time

In this section we describe the code implementation details and training time analysis for DAWMR networks.

C.1 Implementation

The design of DAWMR networks permits the use of parallel computing strategies that result in fast training time. A schematic illustration of our pipeline is given in Figure 5.

Unsupervised feature learning is performed on a traditional multicore CPU. Next, features are extracted for potentially millions of locations distributed across a large 3d image volume with billions to trillions of voxels. In our experiments, this computation is spread across a CPU cluster comprising thousands of cores. Each worker loads image data for the locations it has been assigned, extracts features, and writes the final feature vector to a file or distributed database. Lastly, supervised learning is performed on a single GPU-equipped machine by repeatedly loading a random selection of feature vectors and performing online minibatch gradient updates with a GPU implementation of a multilayer perceptron.

Gradient-based supervised training of deep convolutional networks requires performing forward and backward pass computations through many layers of processing, and the intricate nature of these computations limits the extent of parallelism that can typically be achieved. By learning the feature representation via efficient unsupervised algorithms, DAWMR networks are able to ‘pre-compute’ feature vectors for each example in parallel across a large CPU cluster (in our experiments, this phase of computation can be accomplished in tens of minutes for even one-hundred million examples).

An open source Matlab/C software package that implements DAWMR networks is available online: <http://sites.google.com/site/dawmrlib/>.

C.2 Training Time

Training DAWMR networks with parallel computation hardware (a CPU cluster and GPUs) results in training times on the order of a single day for a single iteration classifier, and multiple days for multiple recursive iterations. This compares favorably with purely supervised multilayer convolutional

networks (typically on the order of weeks for GPU implementations with 3d filters, even without multiscale processing).

An analysis of our pipeline (Figure 5) reveals that the vast majority of time is spent training the multilayer perceptron (MLP). Moreover, during the GPU-based MLP training, most of the time is spent on I/O to retrieve feature vectors from the filesystem for each randomly constructed minibatch. In our experiments, the filesystem was a large-scale EMC Isilon installation accessed via 10-gigabit networking.

Substantial improvements in training time could thus be achieved by additional engineering that simply reduced the overhead associated with accessing feature vectors. In-memory databases, flash storage, and more efficient distributed filesystems are likely to enable such improvements.