Cross Modal Distillation for Supervision Transfer

Saurabh Gupta  Judy Hoffman  Jitendra Malik
UC Berkeley
{sgupta, jhoffman, malik}@eecs.berkeley.edu

Abstract

In this work we propose a technique that transfers supervision between images from different modalities. We use learned representations from a large labeled modality as a supervisory signal for training representations for a new unlabeled paired modality. Our method enables learning of rich representations for unlabeled modalities and can be used as a pre-training procedure for new modalities with limited labeled data. We show experimental results where we transfer supervision from labeled RGB images to unlabeled depth and optical flow images and demonstrate large improvements for both these cross modal supervision transfers.

1 Introduction

Current paradigms for recognition in computer vision involve learning a generic feature representation on a large dataset of labeled images, and then specializing or finetuning the learned generic feature representation for the specific task at hand. Successful examples of this paradigm include almost all state-of-the-art systems: object detection [12], semantic segmentation [28], object segmentation [17], and pose estimation [38], which start from generic features that are learned on the ImageNet dataset [6] using over a million labeled images and specialize them for each of the different tasks. Several different architectures for learning these generic feature representations have been proposed over the years [25][35][3], but all of these rely on the availability of a large dataset of labeled images to learn feature representations.

The question we ask in this work is, what is the analogue of this paradigm for images from modalities which do not have such large amounts of labeled data? There are a large number of image modalities beyond RGB images which are dominant in computer vision, for example depth images coming from a Microsoft Kinect, infra-red images from thermal sensors, aerial images from satellites and drones, LIDAR point clouds from laser scanners, or even images of intermediate representations output from current vision systems e.g. optical flow and stereo images. The number of labeled images from such modalities are at least a few orders of magnitude smaller than the RGB image datasets used for learning features, which raises the question: do we need similar large scale annotation efforts to learn generic features for images from each such different modality?

We answer this question in this paper and propose a technique to transfer learned representations from one modality to another. Our technique uses ‘paired’ images from the two modalities and utilizes the mid-level representations from the labeled modality to supervise learning representations on the paired un-labeled modality. We call our scheme supervision transfer and show that it is able to successfully transfer supervision across modalities. We also show that our technique leads to learning rich semantic concepts in the unlabeled modality, and that for complementary modalities, the intermediate representations are also complementary.

As a motivating example, consider the case of depth images. While the largest labeled RGB dataset ImageNet [6] consists of over a million labeled images, the size of most existing labeled depth datasets is of the order of a few thousands [33][36][22]. At the same time there are a large number of unlabeled RGB and depth image pairs. Our technique leverages this large set of unlabeled paired
images to transfer the ImageNet supervision on RGB images to depth images. Our technique is illustrated in Figure 1. We use a convolutional neural network that has been trained on labeled images in the ImageNet dataset, and use the mid-level representation learned by these CNNs as a supervisory signal to train a CNN on depth images. Our technique for transferring supervision results in improvements in performance for the end task of object detection on the NYUD2 dataset, where we improve the state-of-the-art from 34.2% to 41.7% when using just the depth image and from 46.2% to 49.1% when using both RGB and depth images together.

Though we show detailed experimental results for supervision transfer from RGB to depth images, our technique is equally applicable to images from other paired modalities. To demonstrate this, we show additional transfer results from RGB images to optical flow images where we improve mean average precision for action detection on the JHMDB dataset from 31.7% to 35.7% when using just the optical flow image and no supervised pre-training.

Our technique is a reminiscent of the distillation idea from Hinton et al. [18]. Hinton et al. [18] extended the model compression idea from Caruana and colleagues [2] to what they call ‘distillation’ and showed how large models trained on large labeled datasets can be compressed by using the soft outputs from the large model as targets for a much smaller model operating on the same modality. Our work here is a generalization of this idea, and a) allows for transfer of supervision at arbitrary semantic levels, and b) additionally enables transfer of supervision between different modalities.

2 Related Work

There has been a large body of work on transferring knowledge between different visual domains, belonging to the same modality. Initial work [26, 14, 18, 8, 20] studied the problem in context of shallow image representations. While [26, 14] sought to learn transformations between well labeled source and sparsely labeled target domains, [1] use the source models as a parameter regularizer for target models, [8, 20] combine these two approaches into a single joint optimization problem. Chopra et al. [4] introduced one of the first deep architectures for visual adaptation by replicating feature extraction for each domain and producing intermediate interpolated domains, while Ghifary et al. [10] showed a single layer neural net could be used to learn the feature transformation between simple domain shifts.

More recently, with the introduction of supervised CNN models by Krizhevsky et al. [25], the community has been moving towards a generic set of features which can be specialized to specific tasks and domains at hand [7, 12, 11, 5, 19] and traditional visual adaptation techniques can be used in conjunction with such features [21]. More recently, unsupervised domain adaptation techniques have been introduced which learn to adapt deep representations so as to minimize the discrepancy between the source and target distributions [39, 9, 29].

All these lines of work study and solve the problem of domain adaptation within the same modality. In contrast, our work here tackles the problem of domain adaptation across different modalities. Most methods for intra-modality domain adaptation described above start from an initial set of features on the target domain, and apriori it is unclear how this can be done when moving across modalities, limiting the applicability of aforementioned approaches to our problem. This cross-
model transfer problem has received much less attention, most notable among those include the works from Christoudias et al. [5] and Ngiam et al. [30]. While Christoudias et al. hallucinate the modalities during training time, Ngiam et al. focus on the problem of jointly embedding multiple modalities in a shared feature space. Our work instead transfers generic knowledge learned from a large set of labeled images of one modality to completely unlabeled images from a new modality.

3 Supervision Transfer

Let us assume we have a modality \( \mathcal{M}_d \) with unlabeled data, \( D_d \) for which we would like to train a rich representation. We will do so by transferring information from a separate modality, \( \mathcal{M}_s \), which has a large labeled set of images, \( D_s \), and a corresponding \( K \) layered rich representation. We assume this rich representation is layered although our proposed method will work equally well for non-layered representations. We use convolutional neural networks as our layered rich representation.

We denote this image representation as \( \Phi = \{ \phi^i_{\mathcal{M}_s,D_s} : i \in [1 \ldots K] \} \). \( \phi^i_{\mathcal{M}_s,D_s} \) is the \( i \)-th layer representation for modality \( \mathcal{M}_s \) which has been trained on labeled images from dataset \( D_s \), and it maps an input image from modality \( \mathcal{M}_s \) to a feature vector in \( \mathbb{R}^{n_i} \).

Feature vectors from consecutive layers in such layered representations are related to one another by simple operations like non-linearities, convolutions, pooling, normalizations and dot products (for example layer 2 features may be related to layer 1 features using a simple non-linearity like \( \max \) with \( 0: \phi^2_{\mathcal{M}_s,D_s}(x) = \max(0, \phi^1_{\mathcal{M}_s,D_s}(x)) \)). Some of these operations like convolutions and dot products have free parameters. We denote such parameters associated with operation at layer \( i \) by \( w^i_s \). The structure of such architectures (the sequence of operations, and the size of representations at each layer, etc.) is hand designed or validated using performance on an end task. Such validation can be done on a small set of annotated images. Estimating the model parameters \( w^i_s \) is much more difficult. The number of these parameters for most reasonable image models can easily go up to a few millions. Heretofore, state-of-the-art models require discriminative learning of these parameters using a large labeled training set.

Now suppose we want to learn a rich representation for images from modality \( \mathcal{M}_d \), for which we do not have access to a large dataset of labeled images. We assume we have already hand designed an appropriate architecture \( \Psi = \{ \psi^i_{\mathcal{M}_d} : i \in [1 \ldots L] \} \). The task then is to effectively learn the parameters associated with various operations in the architecture, without having access to a large set of annotated images for modality \( \mathcal{M}_d \). As before, we denote these parameters to be learned by \( W^i_d : i \in [1 \ldots L] \)

In addition to \( D_s \), let us assume that we have access to a large dataset of unlabeled paired images from modalities \( \mathcal{M}_s \) and \( \mathcal{M}_d \). We denote this dataset by \( U_{s,d} \). By paired images we mean a set of images of the same scene in two different modalities. Our proposed scheme for training rich representations for images of modality \( \mathcal{M}_d \) is to learn the representation \( \Psi \) such that the image representation \( \psi^i_{\mathcal{M}_d}(I) \) for image \( I \) matches the image representation \( \phi^i_{\mathcal{M}_s,D_s}(I_s) \) for its image pair \( I_s \) in modality \( \mathcal{M}_s \) for some chosen and fixed layer \( i^* \in [1 \ldots K] \). We measure the similarity between the representations using an appropriate loss function \( f \) (for example, euclidean loss). Note that the representations \( \psi^i_{\mathcal{M}_d} \) and \( \phi^i_{\mathcal{M}_s} \) may not have the same dimensions. In such cases we embed features \( \psi^i_{\mathcal{M}_d} \) into a space with the same dimension as \( \phi^i_{\mathcal{M}_s} \) using an appropriate simple transformation function \( t \) (for example a linear or affine function).

\[
\min_{W^i_d : i \in [1 \ldots L]} \sum_{(I_s,I_d) \in U_{s,d}} f \left( t(\psi^i_{\mathcal{M}_d}(I_d)), \phi^i_{\mathcal{M}_s,D_s}(I_s) \right)
\]

We call this process supervision transfer from layer \( i^* \) in \( \Phi \) of modality \( \mathcal{M}_s \) to layer \( L \) in \( \Psi \) of modality \( \mathcal{M}_d \).

The recent distillation method from Hinton et al. [18] is a specific instantiation of this general method, where a) the two modalities \( \mathcal{M}_s \) and \( \mathcal{M}_d \) are the same, and b) the supervision transfer happens at the very last prediction layer, instead of an arbitrary internal layer in representation \( \Phi \).
Our experiments in Section 4 demonstrate that this proposed method for transfer of supervision is a) effective at learning good representations, b) results in transfer of semantic information, and c) the resulting representation can be complementary to the representation in the source modality $M_s$ if the modalities permit.

4 Experiments

In this section we present experimental results for the NYUD2 dataset where we use color and depth images as the paired modalities, and on the JHMDB video dataset for which we use the RGB and optical flow frames as the two modalities.

Our general experimental framework consists of two steps. The first step is supervision transfer as proposed in Section 3 and the second step is to assess the quality of the transferred representation by using it for a downstream task. For both of the datasets we study, we consider the domain of RGB images as $M_s$ for which there is a large dataset of labeled images $D_s$ in the form of ImageNet [6], and treat depth and optical flow respectively as $M_d$. These choices for $M_s$ and $M_d$ are of particular practical significance, given the lack of large labeled datasets for depth images and optical flow, at the same time, the abundant availability of paired images coming from RGB-D sensors (for example Microsoft Kinect) and videos on the Internet respectively.

For our layered image representation models, we use convolutional neural networks (CNNs) [27, 25]. These networks have been shown to be very effective for a variety of image understanding tasks [7]. We experiment with the network architectures from Krizhevsky et al. [25] (denoted AlexNet), Simonyan and Zisserman [35] (denoted VGG) and Chatfield et al. [3], and use the models pre-trained on ImageNet [6] from the Caffe [24] Model Zoo.

We use an architecture similar to [25] for the layered representations for depth and flow images. We do this in order to be able to compare to past works which learn features on depth and flow images [16, 13]. Validating different CNN architectures for depth and flow images is a worthwhile scientific endeavor, which has not been undertaken so far, primarily because of lack of large scale labeled datasets for these modalities. Our work here provides a method to circumvent the need for a large labeled dataset for these and other image modalities, and will naturally enable exploring this question in the future, however we do not delve in this question in the current work.

We next describe our design choices for which layers to transfer supervision between, and the specification of the loss function $f$ and the transformation function $t$. In all the experiments we report in this paper, we transfer supervision from pool15 layer of one network to another. Experiments in [12] show that the representation at pool15 layers are fairly semantic and may also correspond to object parts. Intuitively, the considerations while picking what layer pair to use for transfer are as follows. First, the source layers $i^s$ that we are transferring from should capture mid-level or high-level semantics rather than low-level image statistics. Low-level image statistics are bound to differ between different modalities and it is unreasonable to expect that they will transfer well (for example, filters in conv1 layers in [25] respond to color which is as such absent in depth images). Second, the layers should be at comparable semantic level, transferring supervision from pool15 to conv1 is going to lead to a very hard learning problem. Finally, one would expect it is best to transfer from essentially the layer closest to the labels to enable as much supervision transfer as possible, though in our initial experiments we found transfer to work better from an intermediate layer as compared to the final layers. We choose pool15 as it also has the advantage that it can be computed in a fully convolutional manner on the whole image at once, resulting in large amounts of shared computation, speeding up the transfer process.

For the function $f$, we use $L2$ distance between the feature vectors, $f(x, y) = \|x - y\|^2_2$. We also tried $f(x, y) = \mathbf{1}(y > \tau) \cdot \log p(x) + \mathbf{1}(y \leq \tau) \cdot \log(1 - p(x))$ (where $p(x) = \frac{\exp(\alpha x)}{1 + \exp(\alpha x)}$, $\mathbf{1}(x)$ is the indicator function), for some reasonable choices of $\alpha$ and $\tau$ but that resulted in worse performance in initial experiments and we did not experiment with it further.

Finally, the choice of the function $t$ varies with different pairs of networks. As noted above, we train using a fully convolutional architecture. This requires the spatial resolution of the two layers $i^s$ in $\Phi$ and $L$ in $\Psi$ to be similar, which is trivially true if the architectures $\Phi$ and $\Psi$ are the same. When they are not (for example when we transfer from VGG net to AlexNet), we adjust the padding in the AlexNet to obtain the same spatial resolution at pool15 layer.
This apart, we introduce an adaptation layer comprising of $1 \times 1$ convolutions followed by ReLU to map from the representation at layer $L$ in $\Psi$ to layer $i^*$ in $\Phi$. This accounts for difference in the number of neurons (for example when adapting from VGG to AlexNet), or even when the number of neurons are the same, allows for domain specific fitting. For VGG to AlexNet transfer we also needed to introduce a scaling layer to make the average norm of features comparable between the two networks.

4.1 Transfer to Depth Images

We first demonstrate how we transfer supervision from color images to depth images as obtained from a range sensor like the Microsoft Kinect. As described above, we do this set of experiments on the NYUD2 dataset [32] and show results on the task of object detection [16]. The NYUD2 dataset consists of 1449 paired RGB and D images. These images come from 464 different scenes and were hand selected from the full video sequence while ensuring ensure diverse scene content [32]. The full video sequence that comes with the dataset has over 400K RGB-D frames.

In all our experiments we report numbers on the standard val and test splits that come with the dataset [32, 16]. Images in these splits have been selected while ensuring that all frames belonging to the same scene are contained entirely in exactly one split.

The downstream task that we study here is that of object detection. We follow the experimental setup from Gupta et al. [16] for object detection and study the 19 category object detection problem, and use mean average precision (mAP) to measure performance.

**Baseline Detection Model** We use the model from Gupta et al. [16] for object detection. Their method builds off R-CNN [12]. In our initial experiments we adapted their model to the more recent Fast R-CNN framework [11]. We summarize our key findings here. First, [16] trained the final detector on both RGB and D features jointly. We found training independent models all the way and then simply averaging the class scores before the SoftMax performed better. While this is counter-intuitive, we feel it is plausible given limited amount of training data. Second, [16] use features from the fc6 layer and observed worse performance when using fc7 representation; in our framework where we are training completely independent detectors for the two modalities, using fc7 representation is better than using fc6 representation. Finally, using bounding box regression boosts performance. Here we simply average the predicted regression target from the detectors on the two modalities. All this analysis helped us boost the mean $AP^b$ on the test set from 38.80% as reported by [16, 15] to 44.39%, using the same CNN network and supervision. This already is the state-of-the-art result on this dataset and we use this as a baseline for the rest of our experiments. We denote this model as 16 + Fast R-CNN'. We followed the default setup for training Fast R-CNN, 40K iterations, base learning rate of 0.001 and stepping it down by a factor of 10 after every 30K iterations, except that we finetune all the layers, and use 688px length for the shorter image side.

Note that Gupta et al. [16] embed depth images into a geocentric embedding which they call HHA (HHA encodes horizontal disparity, height above ground and angle with gravity) and use the AlexNet architecture to learn HHA features and copy over the weights from the RGB CNN that was trained for 1000 way classification [25] on ImageNet [60] to initialize this network. All through this paper, we stick with using HHA embedding $H$ to represent the input depth images, and their network architecture, and show how our proposed supervision transfer scheme improves performances over their technique for initialization. We summarize our various transfer experiments below:

**Does supervision transfer work?** The first question we investigate is if we are able to transfer supervision to a new modality. To understand this we conducted the following three experiments:

1. **no init:** randomly initialize the depth network using weight distributions typically used for training on ImageNet and simply train this network for the final task. While training this network we train for 100K iterations, start with a learning rate on 0.01 and step it down by a factor of 10 every 30K iterations.

2. **copy from RGB:** copy weights from a RGB network that was trained on ImageNet. This is same as the scheme proposed in [16]. This network is then trained using the standard Fast R-CNN settings.

\[\text{We use the term depth and HHA interchangeably.}\]
for VGG to AlexNet transfer by 1

[init], which is consistent with what Gupta et al. We report the results in Table 1. We see that ‘copy from RGB’ surprisingly does better than ‘no init’, which is consistent with what Gupta et al. report in [16], but our scheme for supervision transfer outperforms both these baselines by a large margin from 25.1% to 29.7% on average. We also experimented with using a RGB network Ψ that has been adapted for object detection on this dataset for supervising the transfer and found that this boosted performance further from 29.7% to 30.5% (denoted ‘supervision transfer adapted’ in Table 1, Ψ indicates RGB AlexNet that has been adapted for detection on the dataset). We use this scheme for all subsequent experiments. We visualize the filters from the first layer for these different schemes of transfer in Figure 2, and observe that our training scheme learns reasonable filters and find that these filters are of different nature than filters learned on RGB images.

Is this transfer of supervision semantic? The next question we ask is if our supervision transfer scheme actually transfers semantic information or does it only end up setting up the initial layers in the right ballpark. To answer this question, we conducted the following two experiments.

1. Quality of transferred pool5 representation: The first experiment was to evaluate the quality of the transferred pool5 representation. To do this, we froze the network parameters for layers conv1 through pool5 to be those learned during the transfer process, and only learn parameters in fc6, fc7 and classifier layers during Fast R-CNN training (denoted ‘supervision transfer adapted (ft fc only)’). We see that there is only a moderate degradation in performance for our learned features from 30.5% to 30.0% indicating that the features learned on depth images at pool5 are semantically informative, and that we are able to transfer more than just structure in the lower layers of the network.

2. Improved transfer using better supervising network Φ: The second experiment investigated if performance improves as we improve the quality of the supervising network. To do this, we transferred supervision from VGG net instead of AlexNet[1]. VGG net has been shown to be better than AlexNet for a variety of vision tasks (for example object detection [12] (see arXiv v5)). As before we report performance when freezing parameters till pool5, and learning all the way. We see that using a better supervising net results in learning better features for depth images: when the representation is frozen till pool5 we see performance improves from 30.0% to 32.2%, and when we finetune all the layers performance goes up to 33.6% as compared to 30.5% for AlexNet.

Table 1: We evaluate different aspects of our supervision transfer scheme on the object detection task on the NYUD2 val set using the mAP metric. Left column demonstrates that our scheme for pre-training is better than alternatives like no pre-training, and copying over weights from RGB networks. The middle column demonstrates that our technique leads to transfer of mid-level semantic features which by themselves are highly discriminative, and that improving the quality of the supervisory network translated to improvements in the learned features. Finally, the right column demonstrates that the learned features on the depth images are still complementary to the features on the RGB image they were supervised with.

| Does supervision transfer work? | Is this transfer of supervision semantic? | Are the representations complementary? |
|-------------------------------|----------------------------------------|--------------------------------------|
| no init 22.7                  | copy from RGB (ft fc only) 19.8         | [RGB]: RGB network on RGB images AlexNet 22.3 |
| copy from RGB 25.1            | supervision transfer adapted (ft fc only) AlexNet * → AlexNet 30.0 | [RGB] + copy from RGB 33.8 |
| supervision transfer AlexNet → AlexNet 29.7 | supervision transfer adapted (ft fc only) VGG * → AlexNet 32.2 | [RGB] + supervision transfer adapted AlexNet * → AlexNet 35.6 |
| supervision transfer adapted AlexNet * → AlexNet 30.5 | supervision transfer adapted VGG * → AlexNet 33.6 | [RGB]+ supervision transfer adapted VGG * → AlexNet 37.0 |

3. supervision transfer: train layers conv1 through pool5 from random initialization using the supervision transfer scheme as proposed in Section 3 on the paired RGB and D images from the video sequence from NYUD2 for scenes contained in the training set. We sampled a frame every 0.5 to 1 second. We then plug in these trained layers for training in Fast R-CNN and initialize the fc6, fc7 and classifier layers randomly.

We report the results in Table[1]. We see that ‘copy from RGB’ surprisingly does better than ‘no init’, which is consistent with what Gupta et al. report in [16], but our scheme for supervision transfer outperforms both these baselines by a large margin from 25.1% to 29.7% on average. We also experimented with using a RGB network Ψ that has been adapted for object detection on this dataset for supervising the transfer and found that this boosted performance further from 29.7% to 30.5% (denoted ‘supervision transfer adapted’ in Table[1], Ψ indicates RGB AlexNet that has been adapted for detection on the dataset). We use this scheme for all subsequent experiments. We visualize the filters from the first layer for these different schemes of transfer in Figure[2] and observe that our training scheme learns reasonable filters and find that these filters are of different nature than filters learned on RGB images.

2To transfer from VGG to AlexNet, we use 150K’ transfer iterations instead of 100K. Running longer helps for VGG to AlexNet transfer by 1.5% and much less (about 0.5%) for AlexNet to AlexNet transfer.
Finally, we report the performance of our best performing supervision transfer scheme (VGG) still complementary and using the two together can help the final performance.

4.2 Transfer to Flow Images

We now report our experiments for transferring supervision to optical flow images. We consider the end task of action detection on the JHMDB dataset. The task is to detect people doing actions like catch, clap, pick, run, sit in frames of a video. Performance is measured in terms of mean
average precision as in the standard PASCAL VOC object detection task and what we used for the NYUD2 experiments in Section 4.1.

A popular technique for getting better performance at such tasks on video data is to additionally use features computed on the optical flow between the current frame and the next frame [34, 13], and we use our supervision transfer scheme to learn features for optical flow images in this context.

**Detection model** For JHMDB we use the experimental setup from Gkioxari and Malik [13] and study the 21 class task. Here again, Gkioxari and Malik build off of R-CNN and we first adapt their system to use Fast R-CNN, and observe similar boosts in performance as for NYUD2 when going from R-CNN to Fast R-CNN framework (Table 3). We denote this model as ‘Gkioxari et al. [13]+Fast R-CNN’. We attribute this large difference in performance to a) bounding box regression and b) number of iterations used for training.

**Supervision transfer performance** We use the videos from UCF 101 dataset [37] for our pre-training. Note that we do not use any labels provided with the UCF 101 dataset, and simply use the videos as a source of paired RGB and flow images. We take 5 frames from each of the 9K videos in the train1 set. We report performance on JHMDB test set in Table 3. Note that JHMDB has 3 splits and as in past work, we report the AP averaged across these 3 splits.

We report performance for three different schemes for initializing the flow model: a) **no init** when the flow network is initialized randomly using the weight initialization scheme used for training a RGB model on ImageNet, b) **supervised pre-training** on UCF 101 starting from RGB weights as done by Gkioxari and Malik [13] (denoted by ‘Gkioxari et al. [13]+Fast R-CNN’, and c) **supervision transfer** from an RGB model to train optical flow model as per our proposed method. We see that our scheme for supervision transfer improves performance from 31.7% achieved when using random initialization to 35.7%, which is more than half way towards what fully supervised pre-training can achieve (38.4%), thereby illustrating the efficacy of our adaptation scheme.

**Conclusion** In this paper, we have presented an algorithm for transfer of learned representations from a well labeled modality to new unlabeled modalities using unlabeled paired images from the two modalities. This enables us to learn rich representations on unlabeled modalities and obtain large boosts in performance. We believe the advances presented in this paper will allow us to effectively use new modalities for obtaining better performance on standard vision tasks.

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