Abstract

Manifold theory has been the central concept of many learning methods. However, learning modern CNNs with manifold structures has not raised due attention, mainly because of the inconvenience of imposing manifold structures onto the architecture of the CNNs. In this paper we present ManifoldNet, a novel method to encourage learning of manifold-aware representations. Our approach segments the input manifold into a set of fragments. By assigning the corresponding segmentation id as a pseudo label to every sample, we convert the problem of preserving the local manifold structure into a point-wise classification task. Due to its unsupervised nature, the segmentation tends to be noisy. We mitigate this by introducing ensemble manifold segmentation (EMS). EMS accounts for the manifold structure by dividing the training data into an ensemble of classification training sets that contain samples of local proximity. CNNs are trained on these ensembles under a multi-task learning framework to conform to the manifold. ManifoldNet can be trained with only the pseudo labels or together with task-specific labels. We evaluate ManifoldNet on two different tasks: network imitation (distillation) and semi-supervised learning. Our experiments show that the manifold structures are effectively utilized for both unsupervised and semi-supervised learning.

1 Introduction

The frontiers of computer vision have been reshaped profoundly in the last few years due to the ever wider deployment of convolutional neural networks (CNNs). A cornucopia of CNNs have been developed and now define the state of the art for many vision tasks. On the other hand, manifold learning has been a central concept for many learning algorithms over decades, with applications to tasks as diverse as dimensionality reduction [32, 41], hashing [34], feature encoding [43], clustering [13, 37], semi-supervised learning [2], model imitation [9], and visualization [26]. Thus, it stands to reason to devise methods to utilize manifold structures more effectively in training CNNs.
Figure 1: **ManifoldNet Pipeline.** The bottom panel shows ensemble manifold segmentation (EMS) for the ensemble of pseudo-labels. The top panel features the architecture of the network, which consists of two network streams shared parameters. The left stream is guided by a task-specific loss function (e.g., classification loss for semi-supervised classification and L2 loss for regression) and is trained with samples whose target values are available. The right stream is guided by an ensemble of pseudo classification tasks and trained with the unlabeled samples used for the clustering.

The main challenge to train a CNN with manifold structures is to incorporate the latter’s structure onto the former’s architecture. Manifold structures are often expressed by a graph or an affinity matrix of all data samples. This is inconvenient to use with many CNNs, as these are tailored for classification tasks with crisp class labels. Systems do exist for learning CNNs on graphs [4, 10, 28], which accommodate affinity graphs directly as training data. However, the scalability of this strand of method is limited, since affinity graphs can potentially be large.

In order to seamlessly couple manifold structures with the architecture of modern CNNs, we propose to segment data manifold. It is segmented so that samples that are close to each other fall into the same group or ‘pseudo-class’. The corresponding pseudo-labels are fed to the CNN to train it for classification: grouping similar samples and separating dis-similar ones. This is in line with the aim of manifold learning. Yet, the labels obtained from the segmentation can be noisy due to its unsupervised nature. To mitigate this, we propose ensemble manifold segmentation (EMS) to create an ensemble of segmentations that are accurate individually and mutually diverse.

EMS leads to an ensemble of pseudo classification tasks, which results in an ensemble-task architecture featuring an ensemble of loss functions. Figure 1 shows the architecture of our method. It consists of two copies of the same network, with shared weight parameters. The right stream is trained with unlabeled data and their pseudo-labels as generated from
ensemble clustering; the stream on the left is trained under ‘real’ supervision, with training samples whose real target labels are available. The method is dubbed ManifoldNet. ManifoldNet can be trained with only the right stream or with the two streams jointly, depending on the nature of the tasks. For instance, for unsupervised learning tasks such as dimensionality reduction, hashing and unsupervised network imitation (distillation), one can use only the right stream. For tasks such as semi-supervised classification, the two streams are trained with different training sets, one labeled, one unlabeled. This flexibility greatly increases the applicability of the method.

ManifoldNet translates manifold structures to crisp labels, which gives representational and training advantages with modern CNNs. Apart from being intuitive and easy to implement, ManifoldNet has additional benefits. Compared to manifold learning methods [9, 32, 41], it comes naturally with an out-of-sample ability: the trained CNNs can be used for many tasks, in the same way as standard CNNs can, e.g. as a feature extractor; Compared to deep embedding [42, 46, 48, 49], ManifoldNet is better scalable as it can be trained in a point-wise manner. ManifoldNet is a very general framework and can be easily applied to many different tasks. As Figure 1 shows, much of the work needed to apply it to a new task lies in adopting a task-specific network architecture. The method is orthogonal to the methods [11, 12, 45] for self-learning feature representations. ManifoldNet is evaluated on two different tasks: network imitation and semi-supervised classification. Experiments show that it effectively utilizes manifold structures for both unsupervised and semi-supervised learning.

2 Related Work

Manifold Learning. As mentioned in Section 1, manifold learning has been extensively studied, and numerous approaches have been developed for many different tasks [2, 9, 26, 32, 37]. A large range of manifold properties have been studied, such as Local Linearity [17, 31], Locality [1], and Local Tangent Space Analysis [52]. While having a great success, these methods share a common drawback. That is, they need to solve the Eigen system of an affinity matrix, which limits them to problems of relatively small-scale, with notable exceptions [40]. By contrast, we incorporate the manifold structure by learning non-linear transformations via deep networks, which yield a greater expressiveness, better optimization ability and better scalability.

Network Learning with Graph Embedding. Graph embedding has been extensively studied as a regularization for network learning [42, 46, 48, 49]. While based on different criteria, these methods share the same overall goal: learning feature representations for the target tasks while preserving the mutual relationships between data samples, e.g., neighbors are expected to be neighbors in the new feature space. Excellent results have been obtained for unsupervised learning [15] as well as semi-supervised learning [46, 48]. Our approach has in common with these methods that it recognizes the importance of kernel functions (manifold) for learning in deep neural networks. At the same time, our method differs significantly from that previous work. Those learning methods require as input the Gram matrix of the training samples, which is expensive in terms of storage. This requirement limits the scalability of these methods, as it does to all kernel learning approaches. Our method however, encodes the manifold into an ensemble of pseudo-labels, which is a much lighter representation than the Gram matrix and is easier to feed to a CNN tailored for recognition.

Ensemble Learning and Clustering. Our method learns the representation from an en-
semble of pseudo-labels, thus building itself on Ensemble Clustering (EC). Many excellent approaches have been developed for EC [8, 25, 39]. EC builds a committee of base learners and to find better solutions by maximizing their agreement. Our ensemble manifold segmentation method shares similarity with EC. Other publications close to ours are [8, 21, 39], where images are classified to sub-sampled categories to accumulate distance measures in an ensemble manner. While showing some similarity, none of the approaches learn the metrics nor the features with deep neural networks.

3 Approach

In this section we first describe our ensemble manifold segmentation and then we explain how to train neural networks with the generated pseudo-labels.

3.1 Ensemble Manifold Segmentation

We use an ensemble of pseudo classification tasks to incorporate prior knowledge about manifold structures into the training of a CNN. These tasks need to 1) be automatically constructible from unlabeled data, and 2) assign two semantically similar images to the same pseudo label, in the spirit of manifold learning.

Given an unlabeled dataset of $N$ images, $\mathcal{D} = \{x_1, x_2, \ldots, x_N\}$, we would like to generate an ensemble of pseudo-labels for them. The number of pseudo classes is fixed in advance and is denoted by $Z$. Let’s denote by $T$ the number of segmentation trials of the ensemble, the pseudo-labels then are $\hat{\mathcal{Y}} = \{\hat{\mathcal{Y}}_1, \hat{\mathcal{Y}}_2, \ldots, \hat{\mathcal{Y}}_T\}$ and $\hat{\mathcal{Y}}_t = \{\hat{y}_t^1, \hat{y}_t^2, \ldots, \hat{y}_t^N\}$, where $\hat{y} \in \{1, \ldots, Z\}$.

As desired in manifold learning, the pseudo classes (clusters) need to be intra-pure and inter-distinctive, i.e. samples that are in the same group should preferably belong to the same semantic class, and samples in different groups to different semantic classes. A straightforward solution is to directly apply a clustering algorithm such as k-means to the data samples. However, the assumption of isotropic distributions of samples hardly holds for high-dimensional image features. Inspired by previous works [7, 8], we propose a seeds-based segmentation method. Seed images that are easily separable are sampled first, and a multi-class discriminative segmentation model is then trained on the ‘easy’ samples to quantize the whole manifold.

3.1.1 Seed Image Selection

In each trial $\forall t \in [1, \ldots, T]$, we first identify a small set of seed images for the segmentation. The goal is to hit as many different object classes as possible with these seeds, and to hit the classes safely – avoiding cases where seeds are positioned near class boundaries. Due to the unsupervised nature, we keep the method simple and general. We now present the seed selection heuristic. The algorithm has its basis in the assumptions that seed images are surrounded densely by their neighbors. On the one hand, the algorithm tries to spread out the seed images, i.e. at a relatively large distance from each other (as with manifold learning). On the other hand, ensemble learning theory suggests that members of the ensemble should be highly varied in order to form a powerful committee. This implies that at each round, the seed images should spread out with respect to a standard distance measure, and across different rounds, the sampled seed images should be diverse.
We leverage $k$-means clustering algorithm for this. In each trial, $k$-means is randomly initialized to cluster all samples in $D$ to $Z$ clusters. After convergence, we position seeds to the cluster centres, leading to a small pseudo datasets: $S_t = \{(x_{c1}, 1), (x_{c2}, 2), \ldots, (x_{cZ}, Z)\}$. Although it is possible to train a discriminative segmentation (classification) method with one training sample per pseudo-class, i.e. the sampled seed images, it is beneficial to enrich the data from a single seed image to a prototype set of multiple images for the purpose of learning better intra-class invariance [8, 12, 36]. To this end, the $K$ nearest neighbors of each seed image are introduced into the corresponding pseudo class, i.e. the included neighbors are given the same pseudo-label as the seed image. This data enrichment is in line with manifold learning: neighboring samples are expected to share the same labels. The $Z$ image prototypes with their pseudo-labels are then used to train a discriminative classifier to segment the whole manifold. The seed growing step provides richer training data for the discriminative learning, while avoiding to considerably degrade data quality. The flaws of each such training set are compensated for by those of the other training sets, as they are diverse.

3.1.2 Ensemble Manifold Segmentation

We now explore the utility of the seed sets acquired in Section 3.1.1 to gather information that can be useful for the manifold segmentation. In particular, we train a multi-class discriminative classifier for each trial $t$: $\phi_t(\cdot) : x \rightarrow \hat{y}, \hat{y} \in \{1, \ldots, Z\}$ for each seed set $S_t$. The full data $D$ is then classified by $\phi_t$ to give a class label for every sample: $\hat{y}_i = \phi_t(x_i)$. The resulting class labels of all samples in $D$ in trial $t$ is $\hat{Y}_t$ and the pseudo labels over all $T$ trials are denoted as $\hat{Y} = \{\hat{Y}_1, \ldots, \hat{Y}_T\}$.

The complete algorithm for ensemble manifold segmentation is summarized in Algorithm 1, where $N[x_i, k]$ returns the $k^{th}$ closest neighbor for image $x_i$. We employ logistic regression for the classifier $\phi_t$ as it is efficient and also generalizes well when trained only on a few training samples, which is an important characteristic as we kept the size of the individual seed sets relatively small. The resulting ensemble pseudo-labels $\hat{Y}$ are then used to train neural networks for various vision tasks. It is noteworthy to mention that the dataset $D$ used so far does not require any labels, meaning that no real target values (e.g. class labels, regression values) are used. Therefore, this dataset can be the same as or different from the dataset that comes with target values for an associated supervised learning task (left stream of the network in Figure 1). The learning procedure will be discussed in Section 3.2.

3.2 Learning CNNs with Ensemble Pseudo-Labels

Our goal in this section is to train a CNN to make a prediction $f : \mathcal{X} \rightarrow \mathcal{Y}$. In the classification case, $\mathcal{Y} = \{1, \ldots, C\}$ with $C$ the number of classes, and $l(\cdot)$ is usually the cross-entropy loss function. For a regression task, $\mathcal{Y} = \mathbb{R}$, and $l(\cdot)$ can be the $L_2$ or $L_1$ loss. Standard supervised training proceeds as follows: given a training set with $M$ samples $D_s = \{(x_1, y_1), \ldots, (x_M, y_M)\}$, it minimizes the loss

$$L_s(\theta_s) = \sum_{i=1}^{M} l(y_i, f(x_i, \theta_s)) + \lambda_s \| \theta_s \|.$$  \hspace{1cm} (1)

where $\lambda_s$ is a scaling factor for the regularization and $\theta_s$ is the parameters of the model $f$. In our scenario, this optimization corresponds to learning the left stream of the network in Figure 1.
Algorithm 1: Ensemble Manifold Segmentation

Input: the dataset $\mathcal{D}$.
Output: pseudo-labels $\hat{\mathcal{Y}} = \{\hat{\mathcal{Y}}_1, \hat{\mathcal{Y}}_2, ..., \hat{\mathcal{Y}}_T\}$

for $t = 1 \rightarrow T$

0. Seed positioning: sample $S_t$ by randomly-initialized $k$-means;
1. Seed growing:
   for $z = 1 \rightarrow Z$
     for $k = 1 \rightarrow K$
       $S_t \leftarrow S_t \cup \{N[x_c, k], z\}$
     end for
   end for
2. Train classifier $\phi_t(\cdot) \in \{1 \ldots Z\}$ on $S_t$.
3. Segmenting entire $\mathcal{D}$ by $\phi_t(\cdot)$ for $\hat{\mathcal{Y}}_t$:
   $\hat{\mathcal{Y}}_t = \{\hat{y}_{1,t}, \hat{y}_{2,t}, ..., \hat{y}_{N,t}\}$ and $\hat{y} \in \{1, ..., Z\}$.
end for

Similarly, training a neural network with the generated pseudo-labels $\hat{\mathcal{Y}}$ extracted from the manifold in Section 3.1 can be formulated as minimizing the cost

$$L_m(\theta_m) = \sum_{t=1}^{T} \sum_{i=1}^{N} l(\hat{y}_i^t, \hat{f}_t(x_i, \theta_m)) + \lambda_m \|\theta_m\|.$$  \hspace{1cm} (2)

where $\lambda_m$ is a regularization parameter and $\theta_m$ is the parameters of the model $\hat{f}_t$ for manifold learning. Note that all networks share all the parameters except for the last layer. This optimization corresponds to learning the right stream of the network in Figure 1. The CNN learned with this cost can be considered as a deep counterpart of the conventional manifold learning techniques, such as LLE and ISOMAP, and it can be applied to the same set of applications, such as dimensionality reduction and hashing.

Our pseudo tasks can be considered to encode prior knowledge into a manifold, that can be incorporated into the supervised learning by adding extra cost functions in a multi-task learning framework, as shown in Figure 1. These two learning tasks then jointly train the network. This architecture is especially suitable for semi-supervised learning, where labeled data are used to train the left network in Figure 1, following Equation 1, and unlabeled data for the right network, following Equation 2. This architecture is also useful for tasks where all samples have target values, such as network distillation, as the knowledge represented by the manifold is complementary to the knowledge from these target values. Learning the network in this case equals to minimizing

$$L(\theta) = L_s(\theta_s) + \lambda L_m(\theta_m)$$ \hspace{1cm} (3)

where $\lambda$ is to balance the two cost terms.

The architectures and parameter settings of the networks are explained in Section 4 in the context of specific tasks.
Table 1: The accuracy (%) of image retrieval at a recall of 1. The goal is to fine-tune the pre-trained AlexNet to imitate the pre-trained VGGNet and ResNet as well as possible.

|          | AlexNet ⇒ VGGNet | AlexNet ⇒ ResNet |
|----------|------------------|------------------|
| STL-10   | AlexNet [18] | Ours | VGGNet | AlexNet [18] | Ours | ResNet |
|          | 42.59 | 46.23 | 51.56 | 52.12 | 42.59 | 47.43 | 51.39 | 55.80 |
| CIFAR-100| 5.40 | 5.37 | 6.07 | 5.70 | 5.40 | 11.45 | 6.07 | 7.75 |

4 Learning Tasks

In this work, we evaluate our method in the context of two different tasks: model imitation (unsupervised network distillation), and semi-supervised classification. The same parameter choices are made for all the tasks. Concerning the network training, \( \lambda_s \) and \( \lambda_m \) correspond to a simple weight decay of 0.0005; \( \lambda \) is set to a value such that the losses from the two streams are approximately the same. The parameters of the segmentation method are set as follows: \( Z = 30 \), \( T = 90 \) and \( K = 9 \).

The datasets considered are standard datasets for image classification and retrieval: STL-10 [6], CIFAR-100 [22], Scene-15 [24], Indoor [29], and SUN397 [47]. The details about their usage will be described along with the corresponding tasks.

4.1 Model Imitation

Obtaining models of computational efficiency at test time is crucial, especially for applications where running time and storage space are at a premium. Among others, model imitation (compression or distillation) [5, 9, 18] is one of the most popular approaches towards addressing this problem. The main idea is to use a fast and compact model to imitate the function learned by a better-performing, but slower and larger model. The learned function is expressed usually by its responses over data samples [5, 18] or by a manifold over the data samples [9]. In this work, we adopt a manifold as the expression.

4.1.1 Shallow Network Imitates Deep Network

Usually, deeper networks have a better learning ability but are memory-hungry and slow. We investigate the problem of using shallow networks to imitate deeper networks. We take AlexNet as our shallow network, and VGGNet and ResNet as our deep networks. Given a collection of images, the pairwise distances among them are computed with features from the deep networks (L2 is used as well); these images are then segmented into ensemble pseudo classes; ManifoldNet is trained according to Eq. 2, i.e. the right stream in Fig. 1. The network architecture is instantiated with an AlexNet with its classification layer replaced by an ensemble of pseudo classification layers. The network is then fine-tuned according to the losses of all the pseudo classification tasks.

We compare our method with network distillation [18], which is akin to our method, but imitates the output scores of the teacher (deep) networks. It is noteworthy that our primary interest is to perform model imitation in an ‘unsupervised’ manner, where no labels of the images are used. The task is evaluated on STL-10 and CIFAR-100, for image retrieval. The model is trained with the images from the training sets without using their labels, and the performance is reported on the test sets.

The retrieval results are listed in Table 1. The table shows that both methods improve the student (shallow) network by imitating the ‘response’ of the teacher (deep) network over
a collection of unlabeled images. This implies that even unlabeled data samples can be used to transfer knowledge. The table also shows that our method outperforms network distillation [18] for this task. We acknowledge that the network distillation problem [18] is different from our model imitation considered here, as the latter requires knowledge transfer across datasets as well. Therefore, a comparison to [18] on this task needs to be treated with caution. Nevertheless, [18] has been widely used for this type of knowledge transfer even across different data modalities, e.g. from images to depth [14], and from video to audio [50]. The advantage of ManifoldNet over network distillation for image retrieval is due to the fact that the learning goal of ManifoldNet is in line with distance preservation. Thus, the features it produces are more suitable for similarity measurement.

4.2 Semi-supervised Classification

Recent years have witnessed considerable progress in image recognition due to the advance of deep learning [16, 23, 35]. These methods, however, heavily rely on the quantity of labeled training data. The explosion of visual data, combined with the high cost of human annotation, starts shifting focus towards learning with less supervision. One typical example is semi-supervised classification (SSC) [7, 19, 20, 27, 30, 33, 38, 46], which aims to learn better classifiers with the help of unlabeled data. ManifoldNet is here evaluated for SSC.

Before diving into the experiments, we need to group previous methods into two groups. The first group consists of all manifold-based methods: to ‘regularize’ the learners with manifold structures of unlabeled samples. The methods include Laplacian SVM (LSVM) [3], Harmonic-Function (HF) [53], Ensemble Projection (EP) [7], and Deep Semi-supervised Embedding (DeepSSE) [46]. A comparison to these methods is an apple-to-apple comparison with the aim to show which methods can utilize manifold structures the best. The second group is generative model based approaches [20, 27, 30, 33, 38], which build on the recent success of generative (adversarial) models. They ‘regularize’ the classifier by adding an auxiliary task to the original classification task, such as denoising in [30] and fake-real image classification in [33]. While these methods define the state-of-the-art, they are currently limited to datasets of small images such as CIFAR-10 [22] and SVHN [51] due to the computational complexity. We compare with them on CIFAR-10 and more importantly study the complementarity between our method and those approaches.

Manifold-based Methods. We compare with manifold-based methods on four classification datasets: STL-10, CIFAR-100, Indoor-67 [29] and SUN-397 [47]. The AlexNet and VGGNet pre-trained on ImageNet are used for feature extraction and network fine-tuning. Six competing methods are considered: Logistic Regression (LR), a baseline of Fine-tuned Networks (FTuning), LSVM, HF, EP, and DeepSSE. For LR, LSVM, HF, and EP, the features are directly extracted with the pre-trained AlexNet and VGGNet. For FTuning, the two pre-trained networks are fine-tuned with the annotated data. DeepSSE and ManifoldNet fine-tune the two networks with both labeled and unlabeled data: DeepSSE adds an auxiliary embedding task, while ManifoldNet adds an ensemble of pseudo classification tasks. DeepSSE and ManifoldNet are both implemented with the architecture of AlexNet and VGGNet.

For STL-10 and CIFAR-100, all images of the training sets are used for the training, out of which 30 images per class are used as labeled data. For both Indoor-67 and SUN-397, 80% of the images per class are used as the training data, out of which 30 images per class are taken as labeled data and the rest as unlabeled data. The performance is reported on the other 20% images. The classification results are listed in Table 2. The table shows that our
Table 2: Accuracy of image classification on four datasets. 30 images per class are used as the labeled data, with the rest of the training images as unlabeled data (see text for details). Missing values are due to the high computational complexity.

| Dataset       | AlexNet LR [3] [53] [7] FTuning [46] Ours | VGGNet LR [3] [53] [7] FTuning [46] Ours |
|---------------|------------------------------------------|------------------------------------------|
| STL-10        | 85.5 85.6 80.4 86.0 85.6 86.9 **87.2**  | 91.7 87.4 86.3 92.1 91.6 91.6 **92.4**  |
| CIFAR-100     | 34.0 35.1 34.2 35.8 34.1 37.0 **40.2**  | 36.2 37.2 34.9 39.2 44.1 44.1 **52.9**  |
| Indoor-67     | 50.4 51.2 46.9 52.2 50.0 53.3 **57.8**  | 62.5 63.4 62.1 64.1 63.1 64.8 **67.5**  |
| SUN-397       | 43.5 — — 43.2 44.1 44.7 **45.8**  | 50.3 — — 50.4 50.0 51.0 **52.3**  |

Table 3: Accuracy of image classification on CIFAR-10.

| Method         | Accuracy   |
|----------------|------------|
| Ladder [30]   | 79.60      |
| CatCAN [38]   | 80.42      |
| iGAN [33]     | 81.37      |
| Ours           | 79.7       |
| iGAN+Ours     | **83.38**  |

method outperforms the competing methods of the first group significantly and consistently. The superior performance to LR, LSVM, HF, and EP is mainly due to the fact that ManifoldNet learns task-specific features deeply while these methods train classification models with pre-trained, general features directly. This is also supported by the fact that DeepSSE outperforms these methods as well.

The table also shows that simply training (fine-tuning) a network on the new data does not improve the performance when the amount of labeled data is limited. 30 images per class are not very little, but are still insufficient. This is exactly the scenario where DeepSSE and our method comes to the rescue with a sensibly-designed regularization term from the manifold structures of a large collection of unlabeled data. The table shows that these data-driven auxiliary tasks do help in regularizing the neural networks. Compared to DeepSSE, ManifoldNet turns the ‘embedding’ task into a classification task. Instead of penalizing individual pairs, it maintains an explicit model of the manifold structures with the pseudo classes. The representation provides richer contextual insights of the neighborhood structure. Also, the quadratic growth of the number of pairs hinders the learning efficiency of DeepSSE.

**Generative Model Based Methods.** We compare with the three generative model based methods: Ladder [30], CatCAN [38] and iGAN [33]. Our network architecture is the same as the discriminative part of iGAN [33]. Since all these methods learns the network from scratch, we adapt our method to learn without fine-tuning. It is an iterative process. Initially, the manifold is constructed with the SIFT_llc feature [44]. ManifoldNet is trained using its two streams. After the first round of training, a new manifold will be generated using the just trained features for another round of training. The iteration continues three times as running more times does not provide further improvement.

The results on CIFAR-10 are reported in Table 3, where 400 images per class are used as the labeled data. As the table shows, our method achieves comparable (slightly worse) results to the state-of-the-art methods without using any pre-trained model. The iterative training procedure provides an improvement of 10% and the procedure can be used to ‘jointly’ learn classifiers and manifold structures. Since our method is complementary by nature to these generative model based methods. We further look into combining the two. For this, we start with the trained iGAN model, augment it our pseudo classification tasks, and then train them jointly. The combination improves the accuracy of iGAN from 81.37% to 83.38%.
5 Conclusion

In this work, we have proposed a novel method ManifoldNet to learn neural networks with manifold structures from unlabeled data. ManifoldNet translates the graph-based manifold structures into an ensemble of pseudo classification labels, significantly easing the process of coupling the structure of manifolds and deep neural networks. ManifoldNet can be trained with the generated pseudo classification labels only or with manual annotations jointly. This gives it the flexibility to be applied to various applications. This work evaluated the method on two tasks: model imitation, and semi-supervised classification. Experiments show that ManifoldNet effectively utilizes manifold structures for both unsupervised and semi-supervised learning.

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