LiDAM: Semi-Supervised Learning with Localized Domain Adaptation and Iterative Matching

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Abstract

Although data is abundant, data labeling is expensive. Semi-supervised learning methods combine a few labeled samples with a large corpus of unlabeled data to effectively train models. This paper introduces our proposed method LiDAM, a semi-supervised learning approach rooted in both domain adaptation and self-paced learning. LiDAM first performs localized domain shifts to extract better domain-invariant features for the model that results in more accurate clusters and pseudo-labels. These pseudo-labels are then aligned with real class labels in a self-paced fashion using a novel iterative matching technique that is based on majority consistency over high-confidence predictions. Simultaneously, a final classifier is trained to predict ground-truth labels until convergence. LiDAM achieves state-of-the-art performance on the CIFAR-100 dataset, outperforming FixMatch (73.50% vs. 71.82%) when using 2500 labels.

1 Introduction

Although the amount of data being generated is increasing every year (Mittal and Sangwan 2019), most of this data is unlabeled. Acquiring labels to sufficiently train fully supervised models is often prohibitively expensive and time-consuming. Given that data-driven deep networks require millions of labeled samples to train, there is a growing interest in semi-supervised methods that learn from a combination of a few labeled samples and a large quantity of unlabeled data (Berthelot et al. 2019b; 2019a; Sohn et al. 2020).

We focus on the task of deep image classification. A fundamental component of semi-supervised learning is the detection of clusters that form in the feature projections of unlabeled data. These clusters are assigned pseudo-labels that, when combined with a handful of real labels, can be used to train and update the classifier. The ultimate goal is to group samples together by propagating real labels to nearby samples with a high degree of confidence. In fact, it was recently shown that iteratively applying a combination of clustering and supervised learning (using only pseudo-labels) on a randomly initialized model can achieve remarkable accuracy for image classification (Caron et al. 2018). In our work, we adopt a similar approach but push performance further by borrowing concepts from transfer learning, and domain adaptation. Additionally our method takes as input initial feature representations from a pretrained or a self-supervised model that requires no human-annotated labels (e.g., MoCo (He et al. 2019) or SimCLR (Chen et al. 2020)).

Our work is in large part motivated by the observation that many large datasets, especially those collected from online scraping algorithms (e.g., CIFAR, ImageNet, etc.), exhibit high intra-class variance due to diversity in the domains from which the images arise. For example, images within a given class may be sourced from official product advertisements, low quality mobile captures for social networking, images captured from surveillance feeds at oblique poses, etc. In addition intra-class shifts can also arise from regional trends (e.g., images of different dog breeds popular within different populations, but all labeled dog). Our hypothesis is that by explicitly modeling intra-class domain variance using localized domain adaptation, we improve the likelihood that clusters align with true classes.

We propose a two-stage approach as shown in Figure 1. In the first stage, we begin by generating feature representations from the unlabeled images using a pretrained or self-supervised model. We then apply $K$-means clustering and assign a pseudo-label to each sample based on the cluster ID. For each cluster, a centricity-based confidence measure is used to extract a subset $S_c$ of samples from which two data subsets are selected corresponding to a source and target domain, denoted $S_s$ and $S_t$. Next, a generative domain adaptation model (DAM) is trained to learn domain-invariant feature representations and to predict pseudo-labels in a space with compact clusters. This is followed by an initial alignment between true and pseudo-labels, achieved by feeding labeled samples to DAM, and assigning true labels to all unlabeled data via a majority consistency rule. In the second stage, we perform a proposed self-paced iterative matching technique to train the final classifier to predict true class labels for all unlabeled samples.

Our novel contributions are twofold: i) the use of deep domain adaptation on artificially induced domain shifts to generate high-quality initial data representations and labels; and ii) introduction of a novel iterative scheme to simultane-
We describe in detail our proposed LiDAM approach.

3.1 Unsupervised Clustering

We perform $K$-means clustering on features extracted from each image and assign an initial pseudo-label prediction across two domains, we *locally* adapt features for each class to suppress intra-class domain variances.

**Semi-supervised learning** While a comprehensive survey of the semi-supervised learning literature is beyond scope, here we highlight a few techniques related to our approach. The sample-efficient method proposed in (Lee 2013) assigns pseudo-labels to unlabeled data for classes that are predicted with high probability. These labels are then aligned with true labels using a majority rule to train a network in a supervised fashion. The MixMatch algorithm by (Berthelot et al. 2019b) proposes using low-entropy labels for unlabeled data. Their approach also combines augmented data with labeled data to predict the classes of unlabeled data. This technique was improved in ReMixMatch (Berthelot et al. 2019a) by aligning the distributions of augmentation anchoring techniques, to align marginal distributions between predictions of unlabeled data and true labels, and to align the output of strongly augmented inputs with that of weakly augmented ones. The same authors (Sohn et al. 2020) proposed FixMatch that combines consistency regularization and pseudo-labeling to align the predictions of pseudo labels between weakly and strongly augmented unlabeled images. Our approach is different from these methods in that we initiate our model with a novel combination of unsupervised clustering and localized domain adaptation, and then align pseudo-labels to true labels using a new iterative matching algorithm.

Figure 1: Overview of proposed two-stage method. In stage (a), feature points and pseudo-labels from $K$-means are used to train the Domain Adaptation Model (DAM, red circle). DAM generates an initial prediction of class labels, which are fed to stage (b) where labels and the classifier (green circle) are iteratively updated until convergence. Iterations are shown unrolled for illustration (figure best viewed in color).
Pseudo-labels of Source \( S \), Target \( T \)

**Pseudo-labels of Source \( S \), Target \( T \)**

**Pseudo-labels**

**Confident Centric-Match**

**Label-correction**

**Inferred True labels**

**Confident Centric-Match**

**Stages:** Cold-start

**Iterative matching**

**Classifier Subnet** \( D(\cdot) \)

**Label-correction**

**Inferred True labels**

**Confident Centric-Match**

**Corrected**

**Finetune**

Figure 2: Detailed illustration of our proposed approach. A domain adaptation model trained on pseudo-labels is initially used to predict real class labels for an unlabeled dataset \( T \), solving the cold start problem (dashed loops in red). These predictions are then used initially train a separate classifier \( D(\cdot) \) that is iteratively updated using alternating label mapping mechanisms (solid green loops).

Based on cluster ID. Rather than cluster on features from a randomly initialized model as performed in (Caron et al. 2018), we cluster on the feature space generated from either a model pretrained on a different dataset, or one trained using a self-supervised learning pretext task (He et al. 2019). Next we select from the dataset two subsets that we treat as arising from separate domains. The selection is based on two premises: the first is that compact groups of samples that tightly surround each cluster’s mean location are more likely belong to the same class, as demonstrated in (Garg and Kalai 2017). The second is based on our hypothesis that these points also belong to the same domain. Conversely, points withing each cluster that are far away from the cluster mean are more likely to belong to a different class and also very likely belong to a different domain. These subsets are then used to train a deep Domain Adapation Model (DAM) to learn domain-invariant features that lead to more compact class clusters, and accurate pseudo-label predictions.

### 3.2 Domain Adaptation Model

We adopt the adversarial domain adaption strategy described in (Ganin and Lemptisky 2015). This architecture comprises 3 subnets. First, a subnet \( M(\cdot) \) with parameters \( \theta_m \) learns domain-invariant feature representations. These are fed to both a domain discriminator \( G(\cdot) \) with parameters \( \theta_g \) that distinguishes between source and target domain; and a classifier \( C(\cdot) \) with parameters \( \theta_c \) that predicts class labels. Training proceeds as a two-player minmax game that simultaneously maximises the loss \( L_g \) of \( G(\cdot) \) (encouraging domain-invariant features) while minimizing the loss \( L_c \) of \( C(\cdot) \) (maximizing classification accuracy). The overall network loss is given by:

\[
\mathcal{L}_{ori}(\theta_m, \theta_c, \theta_g) = \frac{1}{N_s} \sum_{i=1}^{N_s} \mathcal{L}_c(y_i, C(M(X_i))) - \frac{\lambda}{N} \sum_{j=1}^{N_t} \mathcal{L}_g(I_j, G(M(X_j)))
\]

(1)

where \( X_i \) and \( y_i \) are input images and pseudo-labels respectively, \( N_s \) and \( N_t \) are the number of samples in the source and target domains respectively, and \( N \) is the total dataset size. Hyperparameter \( \lambda \) balances the importance of classifier loss \( \mathcal{L}_c \) vs. domain discriminator loss \( \mathcal{L}_g \). The binary variable \( I_j \in \{0, 1\} \) denotes whether a sample is from the source or target domain. Network parameters are learned through the min-max optimization shown below,

\[
(\hat{\theta}_m, \hat{\theta}_c, \hat{\theta}_g) = \arg \min_{\theta_m, \theta_c, \theta_g} \mathcal{L}_{ori}(\theta_m, \theta_c, \theta_g),
\]

(2)

Since the overall number of domains present in each class is unknown, we do not know a priori the class overlap between source and target domains. Hence, we adopt a partial domain adaptation technique. In general, aligning the source label space \( L_s \) to the target label space \( L_t \) can result in classification performance decay due to effects from the outlier label space \( L_s \setminus L_t \) of source labels that are not represented in the target domain. We assume a common scenario where \( |L_t| \ll |L_s \setminus L_t| \) (this is reflected in our choice of source and domain set sizes in Section 4). We implement the partial adversarial domain adaptation approach defined in (Cao et al. 2018) by assigning weights on source domain classes to reduce the interference from outlier classes when learning transferable features. The weight \( \mathbf{v} \) is a \(|L_s|\) dimensional vector that enhances weights on \( L_s \cap L_t \) and attenuates weights on \( L_s \setminus L_t \). Specifically, \( \mathbf{v} \) quantifies contributions from each class by averaging the label predictions over target data:

\[
\mathbf{v} = \frac{1}{N_t} \sum_{i=1}^{N_t} \hat{y}_i,
\]

(3)

Note that the weight \( \mathbf{v} \) satisfies \( \sum_{i=1}^{L_t} v_i = 1 \). By normalizing the weight \( \mathbf{v} \) by its maximum value, \( \mathbf{v} / \max(\mathbf{v}) \) small weights are assigned to \( L_s \setminus L_t \). We apply the weight \( \mathbf{v} \) to the classifier \( C(\cdot) \) and the discriminator \( G(\cdot) \) over source domain data to equations (1) and (2) and define losses for partial domain adaptation:
Algorithm 1: Iterative Matching

1. Pretrain(DAM)
2. DAM(T; θd) → I  
3. I → S′c  
4. Initialize(Loop)
5. while AccL >= Acccest do
6. if ModelL not exist then
7. for number of classes do
8. lnew = Map(Iv → Tlv)  
9. Update(R) ← lnew
10. end
11. else
12. Acccest = AccL
13. ModelL = ModelL
14. D(Sc; θd) → I′  
15. I′ → S′c  
16. for number of classes do
17. l′new = Map(S′v → I′lv)  
18. Update(R) ← l′new
19. end
20. end
21. Tune classifier D(R; θd) and finetune with T
22. Save(ModelL, AccL)  
23. end

\[\mathcal{L}_{par}(\theta_m, \theta_c, \theta_g) = \frac{1}{N_s} \sum_{i=1}^{N_s} v_{yi} \mathcal{L}_c(y_i, C(M(X_i))) - \frac{\lambda}{N_s} \sum_{i=1}^{N_s} v_{yi} \mathcal{L}_g(l_i, G(M(X_i))) - \frac{\lambda}{N_t} \sum_{j=1}^{N_t} \mathcal{L}_g(l_j, G(M(X_j))) \]  (4)

where the hyper-parameter \(\lambda\) is same as defined in equation (1) and \(v_{yi}\) is the weight corresponding to the ground-truth label \(y_i\) with source data \(X_i\). The parameters are then learned through min-max optimization:

\[\hat{\theta}_m, \hat{\theta}_c = \arg \min_{\theta_m, \theta_c} \mathcal{L}_{par}(\theta_m, \theta_c, \theta_g),\]

\[\hat{\theta}_g = \arg \min_{\theta_g} \mathcal{L}_{par}(\theta_m, \theta_c, \theta_g).\]  (5)

3.3 Label initialization

Given an initially pseudo-labeled training set \(R\), we identify a subset of samples \(S_c\) for which we have a high degree of confidence in the pseudo-label prediction. This is achieved by selecting the \(k\) neighbors nearest to each cluster centroid based on Euclidean distance. \(S_c\) is randomly divided into a source domain set \(S_s\) and a target domain set \(S_t\). The value of \(k\) is empirically selected to balance pseudo-label and ground-truth label prediction accuracy (explained in more detail in Section 4 and Figure 3).

To start the iterative matching process and address the cold-start problem of predicting ground-truth labels for unlabeled samples, we adopt the following majority consistency approach. We run the small set \(T\) of labeled samples through DAM(\(\cdot\)) to get predicted pseudo-labels. Note that samples from a given true class can map to multiple pseudo-labels. We count the occurrences of pseudo-label predictions within a given true class, and assign to that class the pseudo-label with the majority count. Now every labeled sample has both a true and pseudo label. Next, the loop is closed by reversing this mapping and aligning each pseudo-label with a ground-truth label for all unlabeled samples, as shown in the right half of Figure 2. To this end, we define a function \(Map\) that matches pseudo-class label \(l_p\) to a true class label \(l_t\) in \([0, Z]\) and returns the true label \(l_t\) as correct label \(l_{new}\).

\[l_{new} = Map(I^v → T^v).\]  (6)

To do this, \(Map\) first counts the frequency of the ground-truth labels associated with each group of samples that have the same high-confidence pseudo-label prediction from DAM(\(\cdot\)). Initially, all high confidence pseudo-label predictions are stored in \(S_{c'} = \{x^v_i | P_r(I_i) >= 1 - \alpha, i \in \{1, 2, ..., |T|\}, j \in \{1, 2, ..., Z\}\}\) where \(\alpha\) is a hyper-parameter (\(\alpha = 1e−5\) in our experiments). Then, all samples \(S_{c'}\) with the same pseudo-label prediction \(l_p\) are collected in the set \(x^v_{c'}\). After determining the most frequently occurring ground-truth label \(l_t\), we propagate the ground-truth label to all members of \(x^v_{c'}\) by replacing the pseudo-label with the true class label \(l_t\). After each pseudo-class label has been matched and updated in \(R\), we use this newly labeled dataset to train a new classifier \(D(\cdot)\) (ResNet-50), which is iteratively finetuned with labeled samples \(T\) for downstream classification.

3.4 Iterative matching

After the cold-start initialization using \(T\), classifier \(D(\cdot)\) is able to start inferring true class labels \(I'\) for the initial source set with high centricity-based confidence scores \(S_c\). During each iteration (denoted as a solid green line in Figure 2), the assigned pseudo-label \(S_s\) is updated based on high confidence predictions by \(D(\cdot)\). To achieve this, the mapping rule is in the reverse direction as described in Eq. 6 since \(D(\cdot)\) predicts true labels as opposed to the pseudo-labels predicted by DAM(\(\cdot\)). Thus, \(Map\) follows the same process but maps each pseudo-label \(l_p^{c'}\) of \(S_s\) to a true class label \(l_t^{c'}\) of \(I'\) and returns the true class label as the correct label \(l_{new}^{c'}\).

\[l_{new}^{c'} = Map(S^{c'}_s → I^{c'}_{new}).\]  (7)

where \(l_{t}^{c'}\) is the most frequent inferred true label on \(x^{c'}_{v}\) with associated pseudo-label \(l_{p}^{c'}\), and \(x^{c'}_{v} \in S_{c'}\) and \(S_{c'}\) is an inferred true label set that contains samples with high probability detections from \(D(\cdot)\). That is, 

\(S_{c'} = \{x^v_i | P_r(I_i) >= \)
Table 1: The effect from the size of confident pseudo label set for the performance of Kmeans clustering on CIFAR-10.

| Cluster subset \(|S_c|\) | Total correct \(K\)-means acc. |
|-------------------------|----------------------------------|
| 500                     | 4762                             | 0.9524 |
| 1000                    | 9326                             | 0.9326 |
| 1500                    | 13732                            | 0.9155 |
| 2000                    | 18089                            | 0.9045 |

Table 2: The effect of the size of confident pseudo label set for the performance of Kmeans clustering on CIFAR-100.

| Cluster subset \(|S_c|\) | Total correct \(K\)-means acc. |
|-------------------------|----------------------------------|
| 30                      | 1775                             | 0.5917 |
| 60                      | 3415                             | 0.5692 |
| 90                      | 5052                             | 0.5613 |
| 120                     | 6553                             | 0.5461 |

\[1 - \alpha', i \in 0, 1, 2, ..., |S_s|, j \in 0, 1, 2, ..., Z\] where \(\alpha'\) is a hyper-parameter that thresholds predicted confidence values (\(\alpha' = 1e-2\) in our experiments). Note that \(S_s\) can potentially affect downstream classification performance if the initial \(K\)-means clustering performance is poor. Thus, choosing a good size for \(S_c\) is critical (we explore different sizes for \(S_s\) in our experimental results and in Table 1 and Table 2). Once pseudo-class labels are matched and updated in \(R\) with \(T\), we again fine-tune the classifier \(D(\cdot)\) and continue iterating. As the number of iterations increase, more and more pseudo-labels will be correctly aligned to true labels (as illustrated in Figure 1-b). The classifier \(D(\cdot)\) is thus progressively improved by optimizing the following problem,

\[
\arg \min_{\theta_d} \sum_{i=1}^{\left| R \right|} \mathcal{L}_d(y_i, D(x_i; \theta_d))
\]

where \(\theta_d\) is the parameters of classifier \(D(\cdot)\) with the loss \(\mathcal{L}_d\) for \(x_i \in R\). The iterations conclude when the predicted class labels converge with the ground-truth labels for all samples in \(T\); and the resulting classifier \(D(\cdot)\) is used for predicting true labels for all samples. The process is summarized in Algorithm 1.

4.2 Implementation details

Our approach relies on an initial set of feature representations extracted from the images. We using a ResNet-152 pretrained on ImageNet to both extract feature representations for the \(K\)-means clustering in the first stage, and as the backbone for the classifier in the second iterative matching stage.

We divide \(S_c\) into an 80 / 20 split for the source and target subsets \(S_s\) and \(S_t\) respectively. For selecting the number of ground-truth samples used to train our models, we follow standard practice: for CIFAR-10, the test on ground-truth selections sizes of 250, 1000, and 4000 which comprise images randomly selected from each class in groups of 25, 100, and 400, respectively; for CIFAR-100, ground-truth selections of 2500, 5000, and 10000 are comprised by randomly selecting 25, 50, and 100 images per class, respectively. For our reported image classification tests, we use the standard test data partition from CIFAR-10 and CIFAR-100.

4.3 Evaluation

We first evaluate how well \(K\)-means clustering performs when choosing the closest \(N\) samples around each cluster center (i.e., \(S_c\)). As can be seen from Table 1 and Table 2, different choices of \(N\) lead to different levels of cluster accuracy or purity (i.e., the number of samples with a common ground-truth label that is unique from other clusters). One clear and intuitive takeaway from both of these results is that as the distance increases from the cluster center, the more likely we are to acquire impurities (i.e., samples of different classes). As discussed in Section 3, this is important for two reasons. The first reason is that since the subset \(S_c\) is used for selecting the intra-class source and target domain sets around each cluster which are used to train \(DAM\), any impurity will likely increase inter-class confusion. The second reason is that these samples are expected to be of a singular class when training the final classification model during the iterative matching stage.

To get an insight of how the choice of \(S_c\) and its subdivisions \(S_t\) and \(S_s\) will effect the training performance of \(DAM\), we conducted a series of experiments as shown in Figure 3. In these experiments, \(S_t\) serves as test data except for the experiment shown in Figure 3(c) where we use the standard CIFAR-10 test data partition. We compare two approaches for subdividing \(S_c\) into the source \((S_t)\) and target \((S_s)\) domains. In the first approach, each sample is randomly assigned to a domain based on a predefined ratio (e.g., 80/20
Table 3: Comparison of classification accuracy on CIFAR-10 and CIFAR-100 with baseline models such as II-model (Laine and Valpola 2017), MixMatch (Berthelot et al. 2019b), EnAET (Wang et al. 2019), UDA (Xie et al. 2019), ReMixMatch (Berthelot et al. 2019a), and FixMatch (Sohn et al. 2020). The highest reported accuracies are used for baseline models. Top accuracies that fall within reported error margins are reported in bold.

| Method          | CIFAR-10 250 labels | CIFAR-10 1000 labels | CIFAR-10 4000 labels | CIFAR-100 2500 labels | CIFAR-100 5000 labels | CIFAR-100 10000 labels |
|-----------------|---------------------|----------------------|---------------------|-----------------------|-----------------------|------------------------|
| II-model        | 0.4903              | 0.6945               | 0.8296              | 0.4323                | -                     | 0.6223                 |
| PseudoLabel     | 0.5119              | 0.7082               | 0.8390              | 0.4308                | -                     | 0.6398                 |
| MixUp           | 0.5349              | 0.7494               | 0.8705              | 0.4666                | -                     | 0.6441                 |
| VAT             | 0.6679              | 0.8172               | 0.8926              | 0.6043                | -                     | 0.7202                 |
| MeanTeacher     | 0.5739              | 0.8668               | 0.8989              | 0.6817                | -                     | 0.7328                 |
| MixMatch        | 0.8979              | -                    | 0.9382              | 0.5739                | -                     | 0.7575                 |
| ReMixMatch      | 0.9461              | -                    | 0.9541              | 0.7288                | -                     | 0.7753                 |
| FixMatch (RA)   | 0.9558              | -                    | 0.9579              | 0.7182                | -                     | 0.7752                 |
| LiDAM           | 0.8083              | 0.8904               | 0.9252              | 0.7350                | 0.7514                | 0.7678                 |

Figure 3: Training performance of DAM at various dataset sizes $|S_c|$ on CIFAR-10 using (a) pseudo-labels, (b) ground-truth labels, and (c) test data from CIFAR-10.

Figure 3(b), we use the same partitions used in Figure 3(a), but instead train and predict on ground-truth labels. Here we can see that the model does not suffer from poor K-means pseudo-label assignment and instead leverages the true labels to progressively improve performance as more of it is provided. Finally, in Figure 3(c) we run this same experiment but test performance on the CIFAR-10 test partition. Overall, we conclude from these experiments that the DAM-Random approach performs better than the DAM-Circle approach. DAM is more accurate at predicting pseudo-labels with smaller sizes (e.g., 500) of $S_c$, and lastly DAM performs better than a finetuned ResNet-50 for learning essential features across multi-source domains. Therefore, we select this configuration and combine it with our iterative matching algorithm to test our full LiDAM framework.

**CIFAR-10 Results** We compare our technique with state-of-the-art methods using varying amounts of ground-truth training data. We follow standard practice by randomly sampling 25, 100, and 400 labels per class. A full comparison of results is provided in Table 3. We provide the highest accuracies reported for each method by the original authors. This approach captures the intuition that multiple domains are spread across the each cluster, and so features can be best extracted after performing multiple local domain shifts in random directions. In the second approach, the distance to the cluster center is used to separate the two domains. This is defined by selecting points that fall within or outside an inscribed circle/sphere (i.e., the closest 80% are assigned to the source domain, the remaining 20% to target domain). The intuition behind this approach is that sample points nearest to cluster centroids will likely belong to a single domain; thus features are best extracted by shifting outward to domains in the periphery. As a baseline approach, we compare the performance of each of these experiments to a ResNet-50 model finetuned on $S_c$. In Figure 3(a), we observe the performance of the DAM model at predicting pseudo-labels using both of these partitioning approaches on $S_c$. They key takeaway from this plot is that randomized domain shifts (DAM-Random) result in the extraction of more robust features compared to DAM-Circle and Finetune as the size of $S_c$ increases and its purity decreases (see Table 1). For comparison in
Top accuracies are indicated in bold, including those that fall within the reported error margins. Our approach is competitive but is outperformed in all labeling cases for CIFAR-10.

**CIFAR-100 Results** As seen in Table 3, our proposed method outperforms all other methods on 2500 labels and 5000 labels. On 2500 labels, we observe a 0.6% improvement compared to ReMixMatch and 1.68% improvement compared to FixMatch. Similar to the results on CIFAR-10, we outperform most other methods when using the minimal amount of data (2500 labels) even when other approaches use the all available data (10000 labels). Our method is also a top performer (within error margin) on 10000 labels.

Overall, our method defines a new state-of-the-art performance for CIFAR-100, but performs worse on CIFAR-10. Our main hypothesis for this discrepancy is that for the CIFAR-100 case, the number of samples in each class are small but the domain variance is large. This is likely an optimal scenario for LiDAM which primarily address such domain variance. On the other hand, CIFAR-10 contains fewer classes but a large number of samples per class. Therefore, there is an increased chance that the clusters identified by $K$-means will have accurately identified all samples across all domains, leading to less domain variance in the regions selected around each cluster centroid. Another point worth noting is that that when using a large number of labels such as 10000 labels from CIFAR-100, as shown in Table 3), our method approaches the top accuracy but falls slightly short. One explanation for this small gap is our choice to use ResNet-50 as our backbone, in contrast to other methods. For example, both FixMatch and ReMixMatch use wide ResNet models (Huang et al. 2017) (e.g. Wide ResNet-28-2, Wide ResNet-28-10, etc.) which both perform better than ResNet-50 in their experiments. Our choice of using a ResNet-50 backbone is based on the availability of a pre-trained version of this network.

## 5 Conclusion

We have introduced LiDAM, a two-stage semi-supervised learning approach for deep image classification that combines deep domain adaptation for label initialization with a novel iterative algorithm for updating both labels and classifier parameters. To our knowledge, LiDAM is the first approach that utilizes localized domain adaptation to reduce intra-class domain variance for the purpose of boosting semi-supervised learning. Our method achieves state-of-the-art performance on the CIFAR-100 dataset while achieving competitive performance on CIFAR-10. In future work, we will explore alternative backbone architectures and representation learning methods, including self-supervised approaches that train using pretext tasks. In addition, we will explore the integration of active learning approaches that selectively request labels for the most informative samples.

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