CS482/682 Final Project Report Group 28
Bridging Domains: Harnessing Ensemble and ADDA for Domain Adaptation

Yinong Zhao, Yuan Gao, Emir Syailendra, Star Liu/yzhao120; ygao130; msyaile1; sliu197

1 Introduction

Background Advancements in machine learning have improved image classification, primarily via supervised learning that relies on large labeled datasets. Obtaining such data can be impractical, prompting interest in domain-unsupervised learning.[1]

Related Work Unsupervised domain adaptation concerns the scenario where there are labeled images from the source domain dataset and unlabeled images from the target domain dataset.[2] In the context of deep learning, the task is to learn features from the images of one domain and transfer learned representations to classify unlabeled target domain images. Domain adaptation methods such as Adversarial Discriminative Domain Adaptation (ADDA)[3] address the issue of domain shift by aligning disparate domain features into a common feature space. Additionally, ensemble learning techniques that combine multiple models can also improve classification performance and robustness within a domain adaptation context.[4] Our study implements ADDA and ensemble strategies to enhance the adaptability and accuracy of image classification across various domains.

2 Methods

Dataset We used the Office-Home3 [5], 4 dataset curated by Jose Eusebio et al. This dataset contains 15,500 images of 65 classes of objects common to most homes and offices. There are 4 domains of images. The first three domains, Artistic images, Clip art, and Product images (ACP), were considered as the source domain on which the models were trained. The real-world images (RWI) were the target source images for testing the performance of domain adaptation. Data is augmented through random flipping, resizing, cropping, color jittering, and greyscaling. We normalized the training data, and the same normalization statistics were used for the testing set.

Setup, Training and Evaluation We implemented two methods: 1) ensemble and 2) an ADDA model given their strengths in handling domain adaptation.

The entire ACP dataset was used for training. In the RWI dataset, 70% of it was used to train the ensemble model (using pseudo-labels rather than true labels for domain adaptation), and the rest 30% was used to test the final performance. The ensemble model approach integrated four distinct and robust neural network architectures: SqueezeNet, MobileNet V2, Inception V3, and ResNet18 (Figure 1).

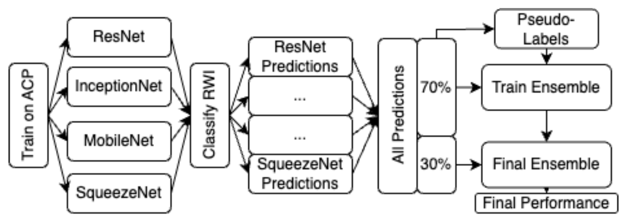


Figure 1: Ensemble method architecture

This approach harnesses the uniqueness of each model to enhance overall performance and reliability. We first trained each model separately on the ACP training data. Then, each model predicts the 70% of the RWI data to generate probabilities for training the ensemble model. Because we are tackling domain adaptation, we cannot use labels from the 70% RWI data. Instead, we generated pseudo-labels from predictions of the 4 individual models, using a weighted average mechanism. The ensemble is a neural network consisting of 4 fully connected layers. The first layer expands the number of inputs into twice the number of features. Each of the later 3 layers reduces the number of features by half before classifying 65 different outcome classes. All the layers except the final layer have a ReLU activation layer. After training the ensemble model on 70% of RWI (using pseudo-labels), it was tested for its final performance using the last 30% of the RWI data. For the ADDA model (Figure 2), we implemented symmetric mapping to establish a unified encoder for both source and target domain data. This approach involved passing the labeled source domain (ACP) through the encoder to train the classifier, thereby learning the label distribution corresponding to the

65 classes. Concurrently, the same source domain data, along with 70% of the RWI data, was passed through the encoder to train the discriminator.

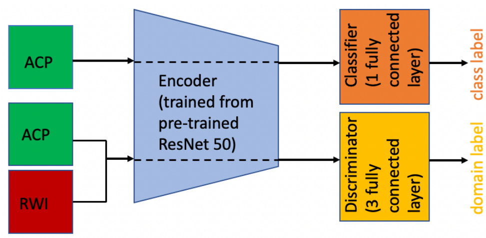


Figure 2: ADDA architecture

This training strategy enabled the model to learn domain-invariant features, as the discriminator's role is to ensure that the encoder's representations are indistinguishable between the source and target domains. After training, the remaining 30% of RWI data was used for final predictions. The encoder is a pre-trained ResNet50. Our rationale for selecting ADDA is its ability to simultaneously train a classifier to classify the 65 category labels while remaining domain-agnostic, meaning it minimizes the representation gap between the source and target domains.

3 Results

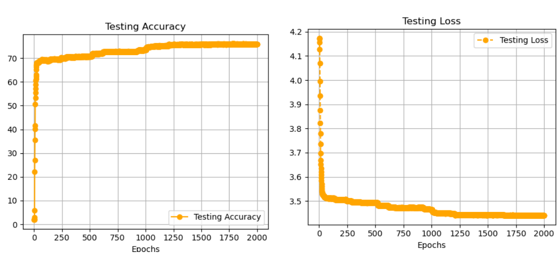
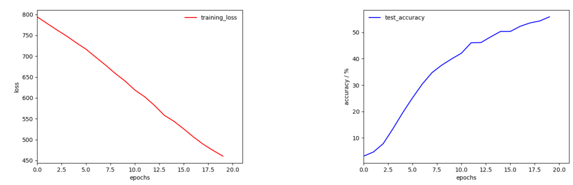


Figure 3: Ensemble architecture

For the ensemble model, we achieved notable improvements in performance metrics (loss and accuracy) over 2000 epochs. By integrating multiple algorithms, the ensemble demonstrated enhanced accuracy (78%) compared to individual models (best at 73.5%). The ADDA model was trained over 20 epochs, constrained by computing resources, focusing on the adversarial training between category classification and domain discrimination. Throughout training, we observed a consistent decrease in the loss on the source domain and a corresponding increase in the testing accuracy on the target domain up to 56% after the final epoch, as illustrated in Figure 4. All our models are staged at our GitHub repository.



(a) Source Domain Training Loss

(b) Target Domain Accuracy

Figure 4: ADDA performance

4 Discussion

In our setup, the ensemble demonstrated superior performance compared to the ADDA model. This can be attributed to several factors inherent in the training approaches. Firstly, the number of training epochs for both models. Due to computational resources constraints, the ADDA model was trained with significantly lower epochs (20 epochs) compared to the ensemble model (2000 epochs). Secondly, the ensemble model combines the strengths of four distinct neural network architectures (SqueezeNet, MobileNet V2, Inception V3, and ResNet 18), each contributing its specialized capabilities to the final prediction. This allows the ensemble to leverage a broad spectrum of features and patterns. To simplify the training process, both the ensemble and ADDA models were trained on a combined dataset of all three domains, treating them as one source. This approach may have neglected the unique attributes of each domain, which impacts the ability to generalize across different types of images. In summary, our analysis showed that ADDA and ensemble method could consistently improve target domain accuracy. As it turns out, most approaches we employed were discussed in a paper that surveyed various domain generalization methods, validating our designs.[6]

References

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[6] Jindong Wang, Cuiling Lan, Chang Liu, Yidong Ouyang, and Tao Qin. Generalizing to unseen domains: A survey on domain generalization. *CoRR*, abs/2103.03097, 2021.