Reconnaissance des formes pour l'analyse et l'interprétation d'images

Homework 2-c: Domain Adaptation

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In many real-world scenarios, we have a labeled dataset at our disposal for training a model, but we want our model to perform well on another unlabeled dataset of a similar nature, though from a different domain. Meanwhile, gathering labels for that unlabeled dataset can be time-consuming and expensive. To address this challenge, many domain adaptation techniques have been developed. In this lab, we will implement one of these techniques. The model will be trained on the MNIST and MNIST-M datasets.

Section 2: Practice

(Q1) Without the use of the GRL, the model achieved the result as following:

	Class loss/accuracy	Domain loss/accuracy
Source	$0.02929/99.05\%$	$3 \times 10^{-5}/100.0\%$
Target	$2.09319/49.16\%$	$0.00047/99.98\%$

Without using a GRL, the training will minimize the loss for both the label and domain classification tasks, as the gradients are updated in the usual descent direction. While the model learns to classify well between classes on the source dataset, it also becomes good at distinguishing between the source and target domains. As a result, the model is not only unable to learn domain-invariant features but also specializes in classifying well on the source domain. Consequently, the model's ability to generalize to the target domain is significantly reduced, as shown in the table with an accuracy of only 49.16% on the target dataset, which is even lower than the results obtained by the naive model.

(Q2) The updates to the model's parameters are influenced by the domain classifier's gradients, which means the model's focus shifts away from purely improving classification performance on the source domain. The model is optimized not only for classification accuracy on the source dataset but also for learning domain-invariant features. This added constraint can slightly reduce its ability to extract features that are perfectly tailored for the source domain, as it sacrifices some specificity for better generalization.

(Q3) The factor $-\lambda$ in the GRL represents the balance between the main classification task and the domain adaptation task. On the one hand, a small λ means that we prioritize the main classification task because only a small part of the reversed gradients from the domain loss contributes to the gradients used to update the model's parameters. In this case, the model can show high performance on the source data but adapt poorly to the target data. On the other hand, a large λ means that the gradients from the domain classifier dominate, which can lead to an instability or, even worse, a significant degradation in the model's performance on the main task. Therefore, a small value of λ is suitable in the early stages of training, when the model needs to focus on learning task-specific features, while a large value is more appropriate in later stages, when the model performs stably on the main task and needs to shift its focus toward achieving domain invariance. In our implementation, we start with a small λ and gradually increase it using a pre-defined schedule, ensuring a smooth transition from learning task-specific features to enforcing domain invariance.

(Q4) Pseudo-labeling is a semi-supervised learning technique that allows a model to be trained on both labeled and unlabeled data. To be more specific, the model is first pre-trained with the labeled dataset. This pre-trained model is then used to predict labels for unlabeled instances. Only predictions with high confidence are selected and combined with the original labeled data to form a new, larger dataset. The model is then retrained with this augmented data set. After that, the process is repeated iteratively until the training converges.