SALAD : Source-free Active Label-Agnostic Domain Adaptation for Classification, Segmentation and Detection
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A.1. Datasets
In this section, we describe the datasets used in our experiments.

0.1. Classification
• MNIST [4]: MNIST is a handwritten digits dataset, with 60,000 samples for training and 10,000 samples for testing. It can be downloaded at http://yann.lecun.com/exdb/mnist/.

• SVHN [10]: SVHN is a house street numbers dataset, and has cropped digits with character-wise ground-truth in MNIST format. It has over 600,000 images and is a much more realistic dataset than MNIST. It can be downloaded at http://ufldl.stanford.edu/housenumbers/.

• VISDA-17 [8]: VISDA is dataset designed for synthetic to real adaptation. The synthetic images are 2D renderings of 3D models generated from various angles and lighting conditions. The real images correspond to natural scene objects. It can be downloaded at http://ai.bu.edu/visda-2017/.

0.2. Segmentation
• GTA5 [9]: GTA5 is a synthetic driving dataset extracted from the computer game Grand Theft Auto. It has 25000 high resolution images. The dataset is available at https://download.visinf.tudarmstadt.de/data/from_games/. It has 19 classes compatible with CityScapes.

• CityScapes [2]: CityScapes is a real driving dataset collected in Europe. It has 2975 high resolution images for training, and 500 images for testing. The dataset is available for download at https://www.cityscapes-dataset.com/. It has 19 classes.

A.2. Synthetic to Real VISDA17 Classification
We conduct experiments on the popular VISDA17 dataset for synthetic to real adaptation. For effective transfer, and to address uncertainty of the target network while sampling, we set $\lambda_G = \lambda_E = 1$ from the second round of sampling. VISDA is a huge dataset with a large variety of samples. Hence, we factor in diversity. The output feature $F_T$ for target samples for clustered using k-means [1]. The mean distance of each target sample from the previously annotated target points gives the diversity score $A_D$. We set the hyperparameter for diversity score $\lambda_K = 1$ from the second round of sampling. On budgets of 10%, and 20%
of the total target samples, we achieve accuracies of 84.8% and 89.3% respectively. Though SALAD does not use any annotated source data, it achieves accuracies on par with prior work using abundant annotated source data (more than 100k samples).

A.3. Implementation details

Hyperparameters: The transformation network $\tau$ is a four layer convolutional neural network with kernel size 3, and dilation and padding set to 1. The weight hyperparameter for $L_T$, is set to 0.1. Our classification models are trained using 1 GPU with 16GB memory. Our document layout detection and segmentation models are trained using 8 GPUs with 16 GB memory each. We use the Stochastic Gradient Descent optimizer for training all our models. All our codes are written using the PyTorch framework. For CityScapes, all images are downsampled by a factor of 2 using bilinear downsampling. Ground truth maps are downsampled by nearest neighbour downsampling. We retain the input image size for our classification experiments. For document layout detection, we resize the images (and appropriately scale the bounding box coordinates) such that the length of the largest size does not exceed 500. We set number of iterations $\text{iter}$ to be equal to 3 for MNIST, 1000 for SVHN, 50 for CityScapes.

Codes: In the interest of reproducibility, we release the codes for GATN, including the code for the transformation network, the guided attention modules, and their incorporation within DeepLabv2 for segmentation. We release the train and eval scripts for segmentation as well. We also provide the scripts for $H_{AL}$ with the supplementary zip file. We will make these scripts publicly available upon acceptance of the paper.

We also provide the links to public repositories that we used in our experiments for running SALAD experiments.

- **Classification**
  - Backbone network: https://github.com/tim-learn/SHOT/blob/master/network.py
  - Please follow the procedure in the deeplab_multi.py script in the supplementary zip file to incorporate GATN within the classification backbone.
  - MNIST and SVHN dataloader: https://github.com/tim-learn/SHOT/blob/master/dataloader
  - VISDA dataloader: https://github.com/VisionLearningGroup/taskcv/tree/master/dataloader
  - Training and eval scripts: Please modify the train and eval script in the supplementary zip file to modify code for classification.

- **Document Layout Detection**
  - Backbone network, train and test scripts: https://github.com/yhenon/pytorch-retinanet
  - PubLayNet dataloader: https://github.com/phamquiluan/PubLayNet/blob/master/dataloader/datasets/publaynet.py
  - DSSE dataloader: Use the PubLayNet dataloader to modify.

- **Semantic Segmentation**
  - Backbone network, train and test scripts: Please check the supplementary zip file.
  - GTA5 and CityScapes dataloaders: https://github.com/wasidennis/AdaptSegNet/tree/master/dataloader

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