# Officail Code for "Efficient Transfer Learning with Spatial Attention and Channel Communication for Unsupervised Domain Adaptation in Object Detection"

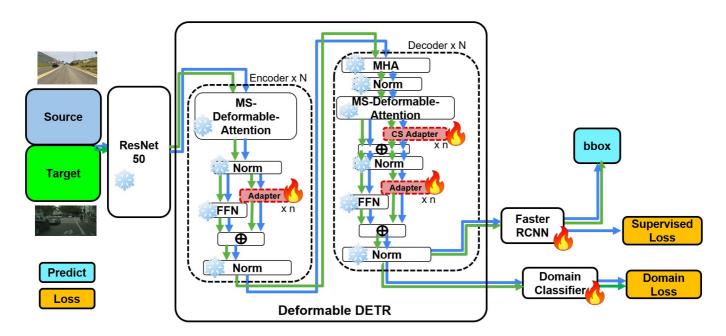
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# Overview

# Code release for the paper:

https://drive.google.com/file/d/19ZY15MAgTQxjjQTUtHEn1vZDbd18qiny/view?usp=sharing



Overview of our proposed architecture, which is based on DeformableDETR. The FG Adapter, depicted in the orange dotted box, is integrated into both the encoder and decoder of Deformable-DETR, while the CS Adapter, shown in the red dotted box, is only in the decoder. The domain classifier, indicated by the purple dotted box, is placed after the decoder.

# **Repository Structure**

```
L— DA_stuff/
    — README.md
     experiment_saved
        CITY2F0GGY_baseline_and_pretrained_on_source
         CITY2FOGGY_oracle_and_trained_on_source_and_target
        — CITY2FOGGY with Dcls
        CITY2FOGGY_with_Dcls_channel_mixing
        CITY2F0GGY_with_Dcls_channel_mixing_spatail_attention
        CITY2F0GGY_with_Dcls_spatail_attention
         SIM2CITY_baseline_and_pretrained_on_source
        SIM2CITY_oracle_and_trained_on_source_and_target
         SIM2CITY_with_Dcls
       ├── SIM2CITY_with_Dcls_channel_mixing
         SIM2CITY_with_Dcls_channel_mixing_spatail_attention
       SIM2CITY_with_Dcls_spatail_attention
      experiment_saved_future_work

    CITY2FOGGY with Dcls channel mixing spatail attention TINY GT LABEL

       SIM2CITY_with_Dcls_channel_mixing_spatail_attention_TINY_GT_LABEL
      figures
        — framework.png
       performance.png
     projects
        — __init__.py
         configs
         - models
            — co detr.py # Architecture are in here
             - _transformer.py # Adapters are in here
      requirements.txt
     - tools
       ├─ train.py
         experiment_CITY2F0GGY.sh
       experiment_SIM2CITY.sh
```

# **Getting Started**

# **System Requirements:**

• Python: version 3.7.11

• GPU: NVIDIA GeForce RTX 3090 Ti

#### Installation

1. Clone the DA\_stuff repository:

```
$ git clone https://github.com/Flame1045/DA_stuff.git
```

2. Change to the project directory:

```
$ cd DA_stuff
```

3. Install the dependencies:

```
$ conda create -n your_repo_name python==3.7.11 -y
$ conda activate your_repo_name
$ conda install pytorch==1.11.0 torchvision==0.12.0 torchaudio==0.11.0
cudatoolkit=11.3 -c pytorch -y
$ pip install -r requirements.txt
$ pip install -U openmim
$ mim install mmengine
$ pip install mmcv-full==1.5.0 -f
https://download.openmmlab.com/mmcv/dist/cu113/torch1.10.0/index.html
$ pip install -v -e .
$ pip install fairscale
$ pip install timm
$ pip3 install natten==0.14.6+torch1110cu113 -f https://shi-
labs.com/natten/wheels
$ pip install tensorboard
```

4. Install pretrained weight:

Cilck here https://drive.google.com/file/d/1ezCc0LeGXj\_7uTVBLKknJWufHAQt0TGL/view?usp=sharing to download and extract and merge files in experiment\_saved. It will looks like the structure below

```
    □ DA_stuff/
    □ experiment_saved
    □ [Experiment_name]
    □ pretrained
    □ XXX.pth # saved pretrained weight
    □ XXX.log # log
    □ XXX.py # config
    □ XXX.pth # saved experiment weight
    □ XXX.pth # saved experiment weight
```

```
$ git clone https://github.com/Flame1045/DA_stuff.git
```

# **Dataset preparation**

Download SIM10k, CITYSCAPES, FOGGY CITYSCAPES from its offical website, convert it to COCO format. Make directory "./data/" and put dataset in below sturcture.

```
☐ DA_stuff/
☐ data
☐ coco
☐ City2Foggy_source # CITYSCAPES dataset
☐ City2Foggy_target # FOGGY CITYSCAPES dataset
☐ SIM2Real_source # SIM10k dataset
☐ SIM2Real_target # CITYSCAPES dataset
```

# **Config Details**

experiment\_saved.SIM2CITY\_baseline\_and\_pretrained\_on\_source

File	Summary						
custom_sim2city_base.py	SIM2CITY pretrained on source						

experiment\_saved.SIM2CITY\_with\_Dcls

Summary
SIM2CITY with domain classifier
Summary
SIM2CITY with spatail attention

File Summary

experiment\_saved.SIM2CITY\_with\_Dcls\_channel\_mixing\_spatail\_attention

File Summary

custom\_sim2city\_unsupervised\_base\_wA\_woCTBV2\_B4.py

custom\_sim2city\_unsupervised\_base\_wA\_woCTBV2\_B4.py

SIM2CITY with channel communication and spatail attention

SIM2CITY with channel communication

experiment\_saved.SIM2CITY\_oracle\_and\_trained\_on\_source\_and\_target

File Summary

experiment\_saved.CITY2FOGGY\_baseline\_and\_pretrained\_on\_source

File Summary

Summary

riie Sum	mary
custom_city2foggy_base.py CITY	2FOGGY pretrained on source
► experiment_saved.CITY2FOGGY_wit	th_Dcls
File	Summary
custom_city2foggy_unsupervised_ba	ase_wA_woCTBV2_B4.py CITY2F0GGY with domain classifier
experiment_saved.CITY2FOGGY_wit	th_Dcls_spatail_attention
File	Summary
custom_city2foggy_unsupervised_ba	ase_wA_woCTBV2_B4.py CITY2FOGGY with spatail attention
experiment_saved.CITY2FOGGY_wit	th_Dcls_channel_mixing
File	Summary
custom_city2foggy_unsupervised_ba	ase_wA_woCTBV2_B4.py CITY2F0GGY with channel communication
► experiment_saved.CITY2FOGGY_wit	th_Dcls_channel_mixing_spatail_attention
File	Summary
custom sity2foggy unsuponised by	CITY2FOGGY with channel
custom_city2foggy_unsupervised_ba	communication and spatail attention
experiment_saved.CITY2FOGGY_ora	acle_and_trained_on_source_and_target
File	Summary
custom_city2foggy_unsupervised_ba	ase_wA_woCTBV2_B4_ORALCLE.py CITY2FOGGY oralcle

# Usage

File

# **Evaluation & Visualization on CITY2F0GGY**

We provide six different experimental setups for evaluating the model on the CITY2FOGGY task. These setups are included in the script `tools/experiment\_CITY2FOGGY.sh`.

The available experiments are:

- CITY2FOGGY\_baseline\_and\_pretrained\_on\_source
- CITY2FOGGY\_oracle\_and\_trained\_on\_source\_and\_target
- CITY2FOGGY\_with\_Dcls\_channel\_mixing\_spatial\_attention
- CITY2FOGGY\_with\_Dcls
- CITY2FOGGY\_with\_Dcls\_channel\_mixing
- CITY2FOGGY\_with\_Dcls\_spatial\_attention

To evaluate a specific experiment, uncomment (# python3 tools/test.py ...) in the desired experiment in the script and run the following command:

\$ bash tools/experiment\_CITY2F0GGY.sh

To visualize specific experiment, add below in script behind python3 tools/test.py ... --eval bbox

```
--show --show-score-thr 0.5 --show-dir your_output_dir
```

#### Evaluation on & Visualization on SIM2CITY

We provide six different experimental setups for evaluating the model on the SIM2CITY task. These setups are included in the script 'tools/experiment\_SIM2CITY.sh'.

The available experiments are:

- SIM2CITY\_baseline\_and\_pretrained\_on\_source
- SIM2CITY\_oracle\_and\_trained\_on\_source\_and\_target
- SIM2CITY\_with\_Dcls\_channel\_mixing\_spatial\_attention
- SIM2CITY\_with\_Dcls
- SIM2CITY\_with\_Dcls\_channel\_mixing
- SIM2CITY\_with\_Dcls\_spatial\_attention

To evaluate a specific experiment, uncomment (# python3 tools/test.py ...) the desired experiment in the script and run the following command:

```
$ bash tools/experiment_SIM2CITY.sh
```

To visualize specific experiment, add below in script behind python3 tools/test.py ... --eval bbox

```
--show --show-score-thr 0.5 --show-dir your_output_dir
```

#### **Training on CITY2F0GGY**

We provide six different experimental setups for training the model on the CITY2FOGGY task. These setups are included in the script `tools/experiment\_CITY2FOGGY.sh`.

The available experiments are:

- CITY2FOGGY\_baseline\_and\_pretrained\_on\_source
- CITY2FOGGY\_oracle\_and\_trained\_on\_source\_and\_target
- CITY2FOGGY\_with\_Dcls\_channel\_mixing\_spatial\_attention
- CITY2FOGGY\_with\_Dcls
- CITY2FOGGY\_with\_Dcls\_channel\_mixing
- CITY2FOGGY\_with\_Dcls\_spatial\_attention

To train a specific experiment, uncomment (# CONFIG= ... to # done) in the desired experiment in the script and run the following command:

```
$ bash tools/experiment_CITY2FOGGY.sh
```

#### **Training on SIM2CITY**

We provide six different experimental setups for training the model on the SIM2CITY task. These setups are included in the script `tools/experiment\_SIM2CITY.sh`.

The available experiments are:

- SIM2CITY\_baseline\_and\_pretrained\_on\_source
- SIM2CITY\_oracle\_and\_trained\_on\_source\_and\_target
- SIM2CITY\_with\_Dcls\_channel\_mixing\_spatial\_attention
- SIM2CITY\_with\_Dcls
- SIM2CITY\_with\_Dcls\_channel\_mixing
- SIM2CITY\_with\_Dcls\_spatial\_attention

To train a specific experiment, uncomment (# CONFIG= ... to # done) the desired experiment in the script and run the following command:

```
$ bash tools/experiment_SIM2CITY.sh
```

# How to modify

CS Adapter is in \_transformer.py line 235

```
class MLP_Adapter_slide8(nn.Module):
```

FG Adapter is in \_transformer.py line 65

```
def build_Adapter(input_dim, hidden_dim, output_dim):
```

Full architecture workflow is in co\_detr.py line 290

```
def forward_train(self, ....
```

# **Future Work**

We incorporate two additional experiments:

1. A tiny percentage of target domain labels is used in our proposed method to evaluate whether the adapter requires labeled data for effective fine-tuning in domain adaptation.

2. We explore a self-training strategy to assess whether the model can improve unsupervised domain adaptation with an enhanced training approach.

# **Pretrained Weight Preparation**

Cilck here https://drive.google.com/file/d/1Wst2HzzjMkm4ryjZTI-GEI\_RUDbo6FC9/view?usp=sharing to download and extract in experiment\_saved\_future\_work. It will looks like the structure below

```
    □ DA_stuff/
    │─ experiment_saved_future_work
    │─ [Experiment_name]
    │─ XXX.log # log
    │─ XXX.py # config
    └─ XXX.py # saved experiment weight
    · · · ·
```

# Tiny Percentage of Target Domain label Experiments

#### **Evaluation on CITY2F0GGY**

We provide one experimental setup for evaluating the model on the CITY2FOGGY task. This is included in the script `tools/experiment\_CITY2FOGGY.sh`.

The available experiments are:

• CITY2FOGGY\_with\_Dcls\_channel\_mixing\_spatail\_attention\_TINY\_GT\_LABEL

To evaluate a specific experiment, uncomment (# python3 tools/test.py ...) in the desired experiment in the script and run the following command:

```
$ bash tools/experiment_CITY2FOGGY.sh
```

# **Results of Cityscapes (Ds)** → **Foggy Cityscapes (Dt)**

Percent of target domain label	person	rider	car	truck	bus	train	motorcycle	bicycle	mAP
0 %	42.7	48.5	56.8	32.7	47.0	32.5	33.0	42.6	42.0
1 %	44.2	50.4	62.7	32.6	46.8	34.9	33.3	42.6	43.4

# **Evaluation on SIM2CITY**

We provide one experimental setup for evaluating the model on the CITY2FOGGY task. This is included in the script `tools/experiment\_SIM2CITY.sh`.

The available experiments are:

#### SIM2CITY\_with\_Dcls\_channel\_mixing\_spatail\_attention\_TINY\_GT\_LABEL

To evaluate a specific experiment, uncomment (# python3 tools/test.py ...) in the desired experiment in the script and run the following command:

\$ bash tools/experiment\_SIM2CITY.sh

# Results of Sim10k (Ds) → Foggy Cityscapes (Dt)

Percent of target domain label	AP
0 %	57.7
1 %	64.8

#### **Training on CITY2F0GGY**

We provide one experimental setup for training the model on the CITY2FOGGY task. This is included in the script `tools/experiment\_CITY2FOGGY.sh`.

The available experiments are:

CITY2FOGGY\_with\_Dcls\_channel\_mixing\_spatail\_attention\_TINY\_GT\_LABEL

To train a specific experiment, uncomment (# CONFIG= ... to # done) in the desired experiment in the script and run the following command:

\$ bash tools/experiment\_CITY2FOGGY.sh

#### **Training on SIM2CITY**

We provide one experimental setup for training the model on the CITY2FOGGY task. This is included in the script 'tools/experiment\_SIM2CITY.sh'.

The available experiments are:

SIM2CITY\_with\_Dcls\_channel\_mixing\_spatail\_attention\_TINY\_GT\_LABEL

To train a specific experiment, uncomment (# CONFIG= ... to # done) the desired experiment in the script and run the following command:

bash tools/experiment\_SIM2CITY.sh

# **Self-training Strategy Implement Thoughts**

#### **Guidelines for Converting This Code to Self-Training**

#### **Step 1: Understand the Current Codebase**

# • Identify Key Components:

- Locate the discriminator and generator/feature extractor (found in projects/models/da\_head.py at line 113).
- Review how adversarial loss is computed and integrated (see projects/models/da\_head.py at line 70).

### Analyze Data Flow:

 Trace how source and target domain data are handled (refer to the config file for each experiment).

### **Step 2: Remove Adversarial Components**

#### • Discriminator Removal:

• Remove the discriminator network and related loss computations.

### • Feature Extractor Adjustment:

• Detach the feature extractor from any adversarial dependencies.

# **Step 3: Implement Pseudo-Labeling**

# • Generate Pseudo-Labels:

- Mask target data according to the MIC paper (https://arxiv.org/abs/2212.01322).
- Use the Student networks to predict target domain labels, including confidence scores.

#### • Filter Pseudo-Labels:

 Apply a confidence threshold to filter pseudo-labels for training, as outlined in the MIC (https://arxiv.org/abs/2212.01322) paper.

# • Assign Pseudo-Labels:

• Store the filtered pseudo-labels for training purposes.

# **Step 4: Modify the Training Loop**

#### • Combine Data:

- Mix labeled source data with pseudo-labeled target data in the data loader.
- Use the Teacher networks to generate predicted target labels.

# • Update Loss Function:

- Modify the loss function to calculate the loss between predicted target labels and pseudo-labels.
   This loss is used to update the Student networks.
- Update the Teacher networks using EMA, as described in the MIC (https://arxiv.org/abs/2212.01322) paper.

# Acknowledgments

- SAPNetV2
- MMdetection
- NATTEN
- Professor Wen-Hsien Fang and Professor Yie-Tarng Chen

#### **Return**