# Homework #2

Deep Learning for Computer Vision NTU, Fall 2022

### **Problems – Overview**

### Image Generation

- Problem 1: GAN (35%) [face dataset CelebA]
- Problem 2: Diffusion models (35%) [digit dataset MNIST-M]
- Unsupervised Domain Adaptation (UDA)
  - Problem 3: DANN (35%) [digit dataset MNIST-M, SVHN and USPS]

Please refer to "Dataset" section for more details about face and digit datasets.

### **Outline**

- Problems & Grading
- Dataset
- Submission & Rules
- Training Tips

## **Problem 1: GAN (35%)**

In this problem, you will need to implement GANs and train them on the **face dataset** (from scratch). In addition, you will need to compute some scores to analyze the performance of your models.

- Please build the following GAN models and train from scratch:
  - A. DCGAN (paper link)
  - **B.** Improve your GAN with any method (modify the model architecture or learning objectives, implement other methods of recent papers, etc.)
- Style-based GANs (e.g., StyleGAN, StyleGAN2) are prohibited
- ☑ Pre-trained model weights are prohibited



### **Problem 1: Evaluation (20%)**

- Generate 1000 face images (by your script) and evaluate them with the following two metrics:
  - (1) Fréchet inception distance (FID)
    - We will use this package for evaluation: <a href="https://github.com/mseitzer/pytorch-fid">https://github.com/mseitzer/pytorch-fid</a>
  - (2) Face Recognition
    - We employ **HOG** algorithm for feature extraction
    - Please refer to the provided script "face\_recog.py"
      - Usage: python3 face\_recog.py --image\_dir <path\_to\_output\_folder>

You should **fix the random seed** in your program such that the generated images are always the same. (for grading)

### **Problem 1: Evaluation (20%)**

- (20%) Baseline:
  - o (10%) Public baseline

Metric	Simple Baseline	Strong Baseline
FID↓	30.00 (2.5%)	27.00 (2.5%)
Face Recognition ↑	85.00 % (2.5%)	90.00 % (2.5%)

FID will be computed with your generated images and the 2,025 face images in the validation set. You are NOT allowed to train your models with validation set.

- (10%) Private baseline TBD (Only FID will be computed in this part)
   FID will be computed with your generated images and the other 2,132 face images (private set)
- You only need to submit one model (either A or B) for the above public / private evaluation.
- Note that your generated images will be evaluated with both validation set and private set.

## Problem 1: Report (15%)

- 1. (5%) Please print the model architecture of method A and B.
  - You can use "print(model)" directly.

2. (5%) Please show the first 32 generated images of both method A and B then discuss the difference between method A and B.



Example for the first 32 generated images

- 3. (5%) Please discuss what you've observed and learned from implementing GAN.
  - You can compare different architectures or describe some difficulties during training, etc.

## **Problem 2: Diffusion models (35%)**

In this problem, you will implement **conditional** diffusion model from scratch and train it on the **MNIST-M dataset** (inside the digit dataset). Given conditional labels 0-9, your model need to generate the corresponding digit images as the following example.



## **Problem 2: Diffusion models (35%)**

• For simplicity, you are encouraged to implement the training/sampling algorithm introduced in the pioneering paper **DDPM** (<u>Denoising Diffusion Probabilistic Models</u>) as follows:

Algorithm 1 Training	Algorithm 2 Sampling
1: repeat 2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$ 3: $t \sim \mathrm{Uniform}(\{1, \dots, T\})$ 4: $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$ 5: Take gradient descent step on $\nabla_{\theta} \left\  \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_{\theta}(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\ ^2$ 6: until converged	1: $\mathbf{x}_{T} \sim \mathcal{N}(0, \mathbf{I})$ 2: <b>for</b> $t = T, \dots, 1$ <b>do</b> 3: $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$ if $t > 1$ , else $\mathbf{z} = 0$ 4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_{\theta}(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$ 5: <b>end for</b> 6: <b>return</b> $\mathbf{x}_0$

 The concept/implementation of conditional diffusion models is similar to conditional GANs (e.g., <u>ACGAN</u>)

## **Problem 2: Evaluation (15%)**

- Sample random noise from normal distribution to generate 100 conditional images for each digit (0-9). Your script should save total 1000 outputs in the assigned folder for further evaluation.
  - You should name your output digit images as the following format:
     (The first character of each filename indicates the corresponding digit label)



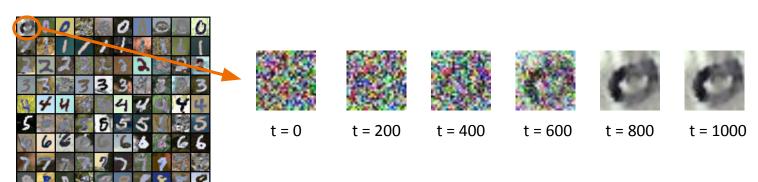
### **Problem 2: Evaluation (15%)**

- We will use a digit classifier to evaluate your generated images by classification accuracy.
  - The source code (digit\_classifer.py) and the model weight (Classifier.pth) is provided in the GitHub template.
    - Usage: python3 digit\_classifier.py --folder <path\_to\_output\_folder>
    - Please follow the saving format in the previous page so that the command can run successfully
- (15%) Baseline:

Metric	Simple Baseline (10%)	Strong Baseline (5%)
Accuracy	80.00 %	88.00 %

## Problem 2: Report (20%)

- 1. (5%) Please print your model architecture and describe your implementation details.
- 2. (5%) Please show 10 generated images **for each digit (0-9)** in your report. You can put all 100 outputs in one image with columns indicating different noise inputs and rows indicating different digits. [see the below example]
- 3. (5%) Visualize total six images in the reverse process of the **first "0"** in your grid in (2) **with different time steps**. [see the below example]
- 4. (5%) Please discuss what you've observed and learned from implementing conditional diffusion model.



### **Problem 3: DANN (35%)**

For unsupervised domain adaptation, you need to implement **DANN** (<u>paper link</u>) for image classification on the **digit datasets**, and consider the following 2 scenarios

(a) MNIST-M  $\rightarrow$  SVHN (b) MNIST-M  $\rightarrow$  USPS (source domain  $\rightarrow$  target domain)

Conduct the following experiments to confirm the effectiveness of your method:

- 1. (Lower bound) Compute the accuracy on target domain, while the model is trained on source domain.
  - Please use source images and labels in "train.csv" for training, target images and labels in "val.csv" to evaluate
- **2. (DANN)** Compute the accuracy on **target** domain, while the model is trained with DANN.
  - You can utilize **both** *images and labels* in the source domain, but **only** *images* in the target domain.
  - Please use source images and labels in "train.csv" + target images in "train.csv" for training, target images and labels in "val.csv" to evaluate
- **3. (Upper bound)** Compute the accuracy on **target** domain, while the model is trained on **target** domain.
  - Please use target images and labels in "train.csv" for training, target images and labels in "val.csv" to evaluate

### **Problem 3: Evaluation (12%)**

- Baseline (classification accuracy on the target domain):
  - (6%) Public baseline:

	MNIST-M → SVHN (3%)	MNIST-M → USPS (3%)
Adaptation (DANN)	40%	76%

• (6%) Private baseline - TBD

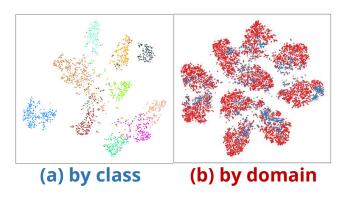
## Problem 3: Report (23%)

1. (5%) Please create and fill the table with the following format in your report:

	MNIST-M → SVHN	MNIST-M → USPS
Trained on source		
Adaptation (DANN)		
Trained on target		

# Problem 3: Report (23%) (cont'd)

- 2. (8%) Please visualize the latent space of DANN by mapping the *validation* images to 2D space with t-SNE. For each scenario, you need to plot two figures which are colored by digit class (0-9) and by domain, respectively.
  - Note that you need to plot the figures of both **2 scenarios**, so **4 figures** in total.



3. (10%) Please describe the implementation details of your model and discuss what you've observed and learned from implementing DANN.

### **Outline**

- Problems & Grading
- Dataset
- Submission & Rules
- Training Tips

### **Tools for Dataset**

#### Download the dataset

(Option 1) Manually download the dataset here

https://drive.google.com/file/d/1YxkObGDlqZM0-9Zq-QMjk7q1vND4UJl3/view?usp=sharing

• (Option 2) Run the bash script provided in the hw2 repository

bash get dataset.sh

### Dataset – Face

#### **Format**

```
hw2_data/
_____ face/
_____ train/ # 38,464 images for training (00000.png ~ 38463.png)
_____ val/ # 2,025 images for validation (38464.png ~ 40488.png)
_____ digits/
```

### Dataset – Face

A subset of human face dataset CelebA

- Images are cropped and downscaled to 64 X 64
- 38,464 training samples (about 20% of complete CelebA)

## **Dataset – Digits**

#### **Format**

```
hw2_data/
     _ digits/
           usps/
                          # images for training and validation (*.png)
              — data/
                 train.csv
                           # labels for training (0, 1, 2, ..., 9)
                         # labels for validation (0, 1, 2, ..., 9)
                 val.csv
                            # sample format
               test.csv
           svhn/
                ...
            mnistm/
                . . .
      face/
```

## **Dataset – Digits**

#### USPS Dataset

# of data: 5,950 / 1,488 (training/validation)

• # of classes: **10** (0~9)

• Image size: 28 \* 28 \* 1

#### MNIST-M Dataset

• # of data: 44,800 / 11,200 (training/validation)

• # of classes: **10** (0~9)

Generated from MNIST

• A subset of MNIST - The digit images are normalized (and centered) in size 28 \* 28 \* 3 pixels





## **Dataset – Digits**

- SVHN Dataset
  - # of data: 63,544 / 15,887 (training/validation)
  - # of classes: **10** (0~9)
  - Real-world image dataset for machine learning development
  - MNIST-like (size: 28 \* 28 \* 3) images centered around a single character

1 You need to deal with the channel difference between datasets by yourself.



### **Outline**

- Problems & Grading
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### **Submission**

- Deadline: 111/10/31 (Mon.) 23:59 (GMT+8)
- Click the following link to get your submission repository with your GitHub account:

### https://classroom.github.com/a/hIUQFicD

- You should connect your Github account to the classroom with your student ID
- If you cannot find your student ID in the list, please contact us (ntudlcv@gmail.com)
- By default, we will grade your last submission (commit) before the deadline (NOT your last submission). Please e-mail the TAs if you'd like to submit another version of your repository and let us know which commit to grade.
- We will clone the **main** branch of your repository.

### **Submission**

- Your GitHub repository **DLCV-Fall-2022/HW2-{GitHub\_ID}** should include the following files:
  - hw2\_<studentID>.pdf (report)
  - hw2\_1.sh (for Problem 1)
  - hw2\_2.sh (for Problem 2)
  - hw2\_3.sh (for Problem 3)
  - your python files (e.g., training code & inference code)
  - your model files (can be loaded by your python file)
- Don't push the dataset to your repo.
- If any of the file format is wrong, you will get zero point.

# Shell Script (Problem 1) – hw2\_1.sh

- Please provide a **script** to the specified directory with your model, and save the 1000 generated images into the specified directory.
- TAs will run your script as shown below:
  - bash hw2\_1.sh \$1
    - \$1: path to the directory for your 1000 generated images (e.g. "~/hw2/GAN/output\_images")
- This section must be finished in **10 mins**, otherwise would be considered as a failed run.

# Shell Script (Problem 2) – hw2 2.sh

- Please provide a **script** to the specified directory with your model, and save the 1000 generated images into the specified directory.
- TAs will run your script as shown below:
  - bash hw2 2.sh \$1
    - \$1: path to the directory for your 1000 generated images (e.g. "~/hw2/Diffusion/output images")
- This section must be finished in **15 mins**, otherwise would be considered as a failed run.



1 You should **follow the filename format** for different digit images as described in Problem 2

# Shell Script (Problem 3) – hw2\_3.sh

- Please provide a script to the specified directory with your model, and save the classification results in the specified csv file.
- TAs will run your script as shown below:
  - bash hw2\_3.sh \$1 \$2
    - \$1: path to testing images in the target domain

```
(e.g. "~/hw2_data/digits/svhn/test" for MNIST-M→SVHN and "~/hw2_data/digits/usps/test" for MNISTM→USPS)
```

- \$2: path to your output prediction file (e.g. "~/test\_pred.csv")
- This section must be finished in **10 mins**, otherwise would be considered as a failed run.
- 1 The format of test\_pred.csv should be the same as test.csv provided in the dataset. (detailed in next page)

# Sample CSV Format (Problem 3)

- Predict class labels for all images
  - Output format: csv file
  - The first row must be: 'image\_name, label'
  - The format should be the same as test.csv

image_name	label
00000.png	0
00001.png	0
00002.png	0
00003.png	0
00004.png	0
00005.png	0
00006.png	0
00007.png	0
00008.png	0
00009.png	0

### **Rules – Submission**

- If your model checkpoints are larger than GitHub's maximum capacity (50 MB), you could download and preprocess (e.g. unzip, tar zxf, etc.) them in hw2\_download.sh.
  - TAs will run 'bash hw2\_download.sh' prior to any inference if the download script exists, i.e. it is **NOT** necessary to create a blank 'hw2\_download.sh' file.
- Do **NOT** delete your model checkpoints before the TAs release your score and before you have ensured that your score is correct.

### **Rules – Submission**

- Please use wget to download the model checkpoints from cloud drive (e.g. Dropbox) or your working station.
  - You should use **-O argument** to specify the filename of the downloaded checkpoint.
  - Please refer to this <u>Dropbox Guide</u> for a detailed tutorial.
- Google Drive is a widely used cloud drive, so it is allowed to use gdown to download your checkpoints from your drive.
  - It is also recommended to use -O argument to specify the filename.
  - Remember to set the permission visible to public, otherwise TAs are unable to grade your submission, resulting in zero point.
  - If you have set the permission correspondingly but failed to download with **gdown** because of Google's policy, TAs will manually download them, no worries!!

### **Rules – Environment**

- Ubuntu 20.04.1 LTS
- NVIDIA GeForce RTX 2080 Ti (11 GB)
- GNU bash, version 5.0.17(1)-release
- Python 3.8

### Rules – Environment

- Ensure your code can be executed successfully on **Linux** system before your submission.
- Use only **Python3** and **Bash** script conforming to our environment, do not use other languages (e.g. CUDA) and other shell (e.g. zsh, fish) during inference.
  - Use the command "python3" to execute your testing python files.
- You must NOT use commands such as sudo, CUDA\_VISIBLE\_DEVICES or other commands to interfere with the environment; any malicious attempt against the environment will lead to zero point in this assignment.
- You shall **NOT** hardcode any path in your python files or scripts, while the dataset given would be the absolute path to the directory.

# Rules – Packages

• numpy: 1.23.1

• torch: 1.12.1

• torchvision: 0.13.1

• scikit-learn: 1.1.2

• timm: 0.6.7

• transformers: 4.21.3

and other standard python packages

• matplotlib: 3.5.3

• pillow: 9.2.0

• imageio: 2.21.2

• scipy: 1.9.1

• scikit-image: 0.18.1

• pandas: 1.5.0

• face-recognition: 1.3.0

• tqdm, gdown, glob, yaml

• E-mail or ask TA first if you want to import other packages.

## Rules – Packages

- Do not use **imshow()** or **show()** in your code or your code will crash.
- Use **os.path.join** to deal with path as often as possible.

# Rules – Policy

- Late policy: We provide a total of three free late days for all four homework submissions this semester. After that, late homework will be deducted by 30% each day.
- Students are encouraged to discuss the assignment, but you must complete the
  assignment by yourself. TA will compare the similarity between everyone's assignment.
  Any form of cheating or plagiarism will not be tolerated, which will also result in F for
  students with such misconduct.
- Please specify, if any, the **references** for any parts of your HW solution in your report (e.g., your collaborators or the GitHub source code).
- Using external dataset is forbidden for this homework.

### Rules – Code modification

- If your code cannot be executed, you have a chance to make minor modifications to your code. After modifying your code,
  - If we can execute your code, you will receive a **30% penalty** in your model performance score.
  - If we still cannot execute your code, no points will be given.
- TAs will release the log of execution after grading, please check.
  - Email the TAs if something goes wrong in your submission.

## How to find help

- Google!
- Use TA hours (please check <u>course website</u> for time/location)
- Post your question to NTU COOL
- Contact TAs by e-mail: <a href="mailto:ntudlcv@gmail.com">ntudlcv@gmail.com</a>

### DOs and DON'Ts for the TAs (& Instructor)

- Do NOT send private messages to TAs via Facebook.
  - TAs are happy to help, but they are not your tutors 24/7.
- TAs will NOT debug for you, including addressing coding, environmental, library dependency problems.
- TAs do NOT answer questions not related to the course.
- If you cannot attend the TA hours, please email the TAs to schedule an appointment instead of stopping by the lab directly.

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## **Training Tips – GAN**

Well known tips and tricks published on GitHub.

It is suggested that you take a look before you start training.

### TA's experience and hints

- Surveying related papers and using similar architectures may help.
- Trace the accuracy of discriminator network to see if Gnet and Dnet performance matches.
- Improved GAN algorithm is harder to implement but easier to train (e.g. WGAN, WGAN-GP)

**GAN** is often difficult to train and tune, starting this part early may help a lot.