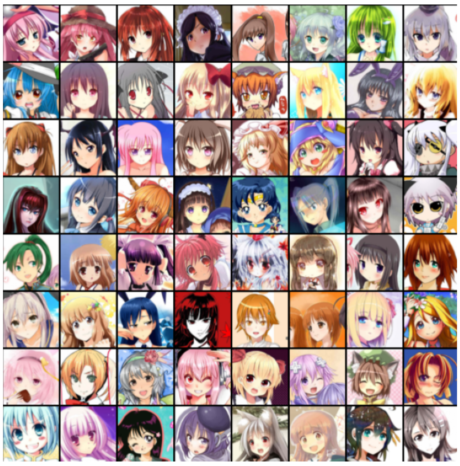
Deep Learning (Homework 2)

Due date : 2023/5/19 23:59:00 (Hard Deadline)

1 Image Generation

1.1 Generative Adversarial Network (15%)

In this exercise, you will implement a Deep Convolutional Generative Network (DCGAN) [1] to synthesis images by using the **anime faces dataset** with the examples shown below.

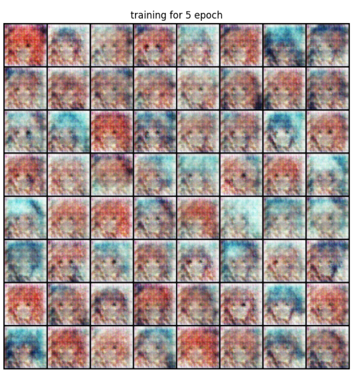


1. Construct a DCGAN with GAN objective, you can refer to the tutorial website provided by PyTorch for implementation.

$$\max_D \mathcal{L}(D) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}}[\log D(\boldsymbol{x})] + \mathbb{E}_{z \sim p_{\boldsymbol{z}}}[\log(1 - D(G(\boldsymbol{z})))]$$
$$\min_G \mathcal{L}(G) = \mathbb{E}_{z \sim p_x}[\log(1 - D(G(\boldsymbol{z}))]$$

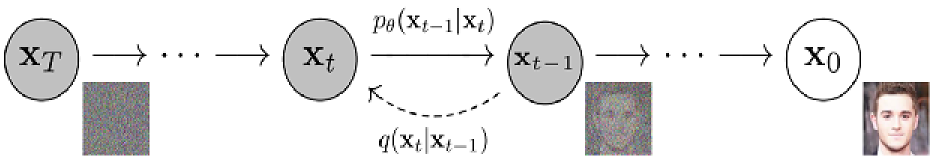
   (a) **Draw** some samples generated from your generator at different training epochs. For example, you may show the results when running at 5^{th} and the final epoch 100. (10%)

   (b) The Helvetica Scenario (or so-called Mode Collapse) often happens during the training procedure of GAN. Regardless of the value of the input random noise $\boldsymbol{z}$, the generator will tend to generate the same sample (or equivalently collapse to the same mode). Please explain why this problem occurs and how to avoid it. (5%) We suggest you can read the original paper and do the discussion.



1.2 Denoising Diffusion Probabilistic Model (25%)

In this exercise, you will implement a Denoising Diffusion Probabilistic Model (DDPM) [2] to generate images by the provided **anime faces dataset**. The Figure below shows the process of diffusion model where the model consists of a forward process which gradually adds noise, and the reverse process which transforms the noise back into a sample from the target distribution. Here are the link 1 and link 2 to the detailed introduction to diffusion model.



1. Construct the DDPM by fulfilling the 2 TODOs and follow the instruction in sample section. Notice that you are not allowed to directly call the library or API to load the model. (20 %)
   (a) **Draw** some generated samples based on diffusion steps $T = 500$ and $T = 1000$. We will provide the **pre-trained weights** which are trained with 500 and 1000 steps. Hint: In the paper, the steps start at 1.
   (b) **Discuss** the results based on different diffusion steps. (5%)

1.3 Comparison between GAN and DDPM (10%)

1. Both GAN and DDPM are generative models. Figure 1 shows the randomly generated samples by using GAN (left) and DDPM (right). Please describe the pros and cons of these two models. (10%)

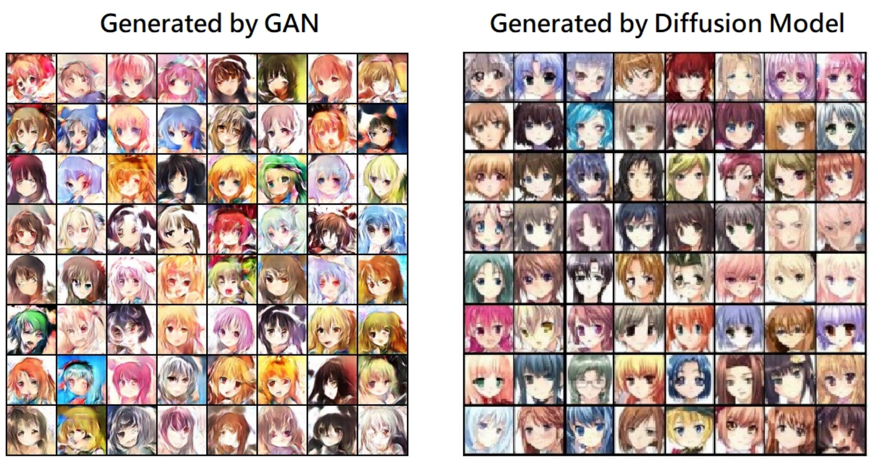


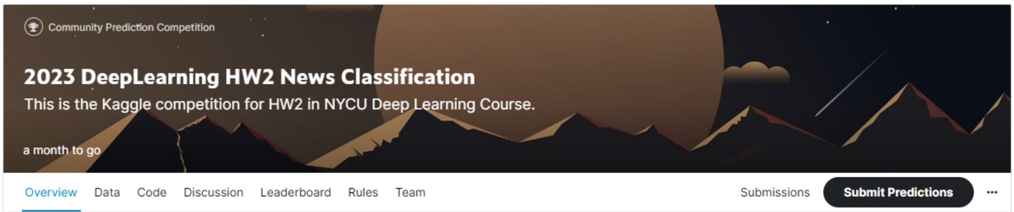
Figure 1: Examples of the generated images from GAN and diffusion model

2 Document Classification

To start this problem, some preliminary steps need to be conducted first:

1. **Join the in-class competition on Kaggle (Here)**
   (or search 2023 DeepLearning HW2 News Classification in Kaggle)
2. **Download the data and check for the description**
3. **You may allow changing your team name to student id after first submission.**

In this problem, you are given a csv file train.csv gathered from more than 2000 news sources from HuffPost, containing the corresponding Label, Headline, and Description. You are required to implement a Transformer to correctly classify the news documents in test.csv and submit the classification result to the Kaggle competition.



2.1 Data Preprocessing (10%)

In this homework, you cannot directly use high-level API to help you process the text data. You are asked to convert a text string into a list of integers by these packages: FastText, TorchText, NLTK, spaCy or Gensim.

1. How do you choose the tokenizer for this task? Could we use the white space to tokenize the text? What about using the complicated tokenizer instead? Make some discussion. (5%) (You might want to explain it by showing the performance comparison with different tokenizer. If you are not familiar with tokenizer, check (`https://www.analyticsvidhya.com/blog/2019/07/how-get-started-nlp-6-unique-ways-perform-tokenization/`))
2. Why we need the special tokens like ⟨pad⟩, ⟨unk⟩? (2%)
3. Briefly explain how your procedure is run to handle the text data. (3%) (e.g. Which tokenizer do you choose? Why? What is your min_count setting? etc.)

2.2 Transformer (40%)

Build the Transformer (using high-level API is forbidden) to solve this task and answer the following questions. (Hint: You might want to read this tutorial first (`https://pytorch.org/tutorials/beginner/transformer_tutorial.html`))

1. Pass the Baseline on the Kaggle in-class competition (Public). (15%)
2. Discuss the model structure or hyperparameter setting in your design. (5%) (e.g. hyper-parameters of transformer: d_model, nhead, d_hid , nlayers, dropout, etc. Why do you choose this setting?)
3. Kaggle Challenger Award! After Kaggle competition, the private leaderboard will reflect the final standings. In private leaderboard, you will be finally recognized as
   - Challenger (10%): Pass the Advanced Line
   - Second prize (5%): Pass the Baseline
   - Consolation prize (5%): Join Kaggle competition and pass Random Line

Hint

You might want to follow these steps to start your work:

1. Tokenize the given text data with some off-the-shelf software.
2. Build the vocabulary (like the dictionary object in python) to map the token into some unique ID.
3. Select the pretrained embedding (Glove, Fasttext, Word2vec) as the initialization of your embedding layer. (Not necessary, but recommended)
4. Construct your transformer model and finally end up with some simple feed forward module.
5. Choose the suitable optimizer (Adam might be not suitable) and activation function (ReLU might be not suitable. Try Tanh or Swish?)
6. Try some tricks like learning rate scheduler.
7. Check some tutorial such as Here.

(Bonus) Prompt-based Learning

- In this part, you are given two tsv files from Stanford Sentiment Treebank v2 (SST2). You need to implement prompt-based learning with Transformer Encoder (**Hybrid prompt** [slide]). You can refer to this paper for understanding the purpose of soft-prompt tuning.
- There is an existing Python library called OpenPrompt which providing the tutorials of prompt-based learning implementation. In this part, you can follow the steps in tutorial and fulfill the TODO in the provided bonus.ipynb

OpenPrompt

An Open-Source Framework for Prompt-learning.

1. Show the final loss and accuracy of the training and test data.(15%)

3 Rule

- The homework has two problems and separate into three parts:
  - **HW 2-1 is for Image generation**:
    Please submit **hw2_1_<StudentID>.ipynb** file which needs to contain all the results, codes, and reports for each exercise (e.g. **hw2_1_0123456.ipynb**).
  - **HW 2-2 is for Document Classification**:
    Please submit one zip file named **hw2_2_<StudentID>.zip** contains
    - hw2_2_<StudentID>.ipynb
    - submission.csv
    - train.csv
    - test.csv

    You can refer to expected_result_of_hw2-2.zip on E3 for more easily understanding.
  - **Bonus is for prompt-based learning**:
    This is optional. If you have finished the part, please submit extra ipynb file named **bonus.ipynb**
- Implementation will be graded by
  - Completeness
  - Algorithm correctness
  - Discussion and analysis
- Only Python implementation is acceptable.
- Kindly suggest using GPU to run the code! You can refer to the Colab tutorial in E3.

References

[1] Alec Radford, Luke Metz, and Soumith Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," in *Proc. of International Conference on Learning Representations*, 2016.

[2] Jonathan Ho, Ajay Jain, and Pieter Abbeel, "Denoising diffusion probabilistic models," *Advances in Neural Information Processing Systems*, vol. 33, pp. 6840–6851, 2020.