

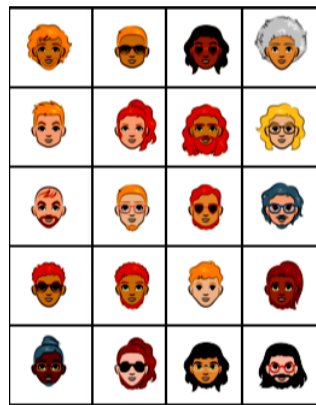


Deep Learning (Homework 3)

Due date : 6/16/2019

- **Homework submission** – Please zip each of your **source code** and **report** into a single compress file and name the file using this format : **HW3_StudentID_StudentName.zip** (rar, 7z, tar.gz, ... etc are *not* acceptable)

In this homework, you will use the cartoon character faces dataset. The dataset contains 10000 face images. All the images are with size of 500×500 . You will use this dataset for the unsupervised image generation as shown bellow



1. Cartoon Character Generation

In this exercise, you will construct a **Variational Autoencoder (VAE)** for image reconstruction by the provided animation faces dataset.

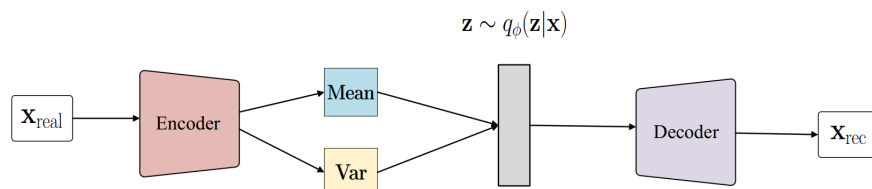


Figure 1: Structure of VAE

VAE paper can be downloaded [here](#). You should preprocess the images such as resizing or cropping by yourself before implementation.

- Describe** in details how to **preprocess images** (such as resize). Implement a VAE for image reconstruction by using convolution layers or fully connection layers. You need to **design** the network architecture and show it in the report. Finally, plot the **learning curve** in terms of loss function or negative evidence lower bound.

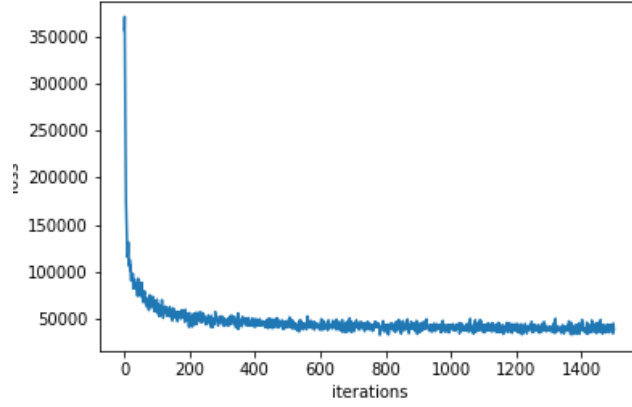


Figure 2: Learning curve of VAE

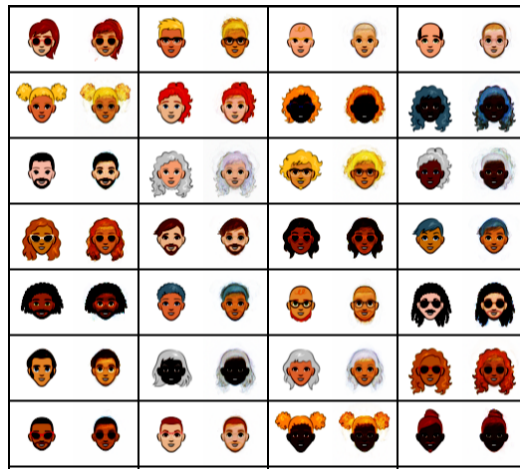


Figure 3: Reconstruction samples using VAE, left one in each pair is ground truth, right one is reconstructed image

- ii. Show some examples reconstructed by your model.
- iii. Sample the prior $p(\mathbf{z})$ to generate some examples when your model is well-trained with convergence.

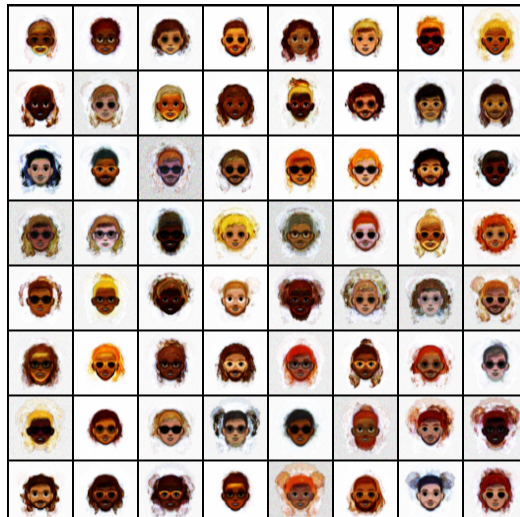


Figure 4: Samples drawn from VAE

2. Style Transfer

In this exercise, you will implement a **cycleGAN** to transfer the American cartoon character into the Japanese animation style, and vice versa. There are 10000 images in both folder “cartoon” and folder “animation”. CycleGAN paper can be downloaded [here](#). The example pytorch codes are provided as `cycleGAN_train.py` and `cycleGAN_test.py`. You only need to fill up **TODO** parts we marked in the code.

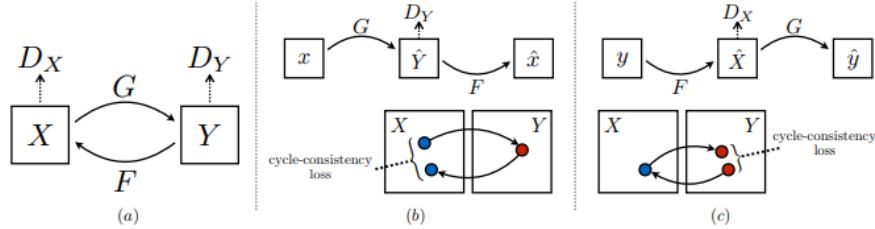


Figure 3: (a) Our model contains two mapping functions $G : X \rightarrow Y$ and $F : Y \rightarrow X$, and associated adversarial discriminators D_Y and D_X . D_Y encourages G to translate X into outputs indistinguishable from domain Y , and vice versa for D_X and F . To further regularize the mappings, we introduce two *cycle consistency losses* that capture the intuition that if we translate from one domain to the other and back again we should arrive at where we started: (b) forward cycle-consistency loss: $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$, and (c) backward cycle-consistency loss: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$

Figure 5: Structure of cycleGAN

- i. Construct a cycleGAN with the loss function below. Plot the learning curve of both generators and discriminators. You can sum up the loss of two generators and plot in one curve.

$$\begin{aligned}\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) &= \mathbb{E}_{y \sim p_{\text{data}}(y)} [\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log(1 - D_Y(G(x)))] \\ \mathcal{L}_{\text{cyc}}(G, F) &= \mathbb{E}_{x \sim p_{\text{data}}(x)} [\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)} [\|G(F(y)) - y\|_1] \\ \mathcal{L}(G, F, D_X, D_Y) &= \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda \mathcal{L}_{\text{cyc}}(G, F) \\ G^*, F^* &= \arg \min_{G, F} \max_{D_X, D_Y} \mathcal{L}(G, F, D_X, D_Y)\end{aligned}$$

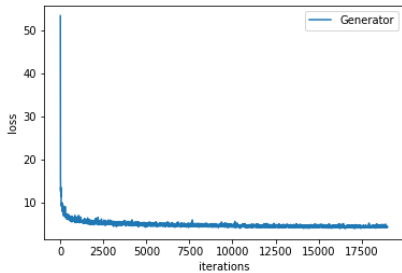


Figure 6: Loss curve for generators

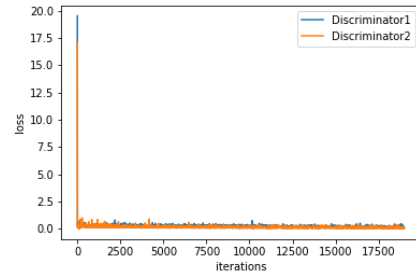


Figure 7: Loss curve for discriminators

- ii. Please sample some cartoon images in animation style and animation images in cartoon style. Show your results and make some discussion in the report.



Figure 8: Samples of cartoon images in animation style

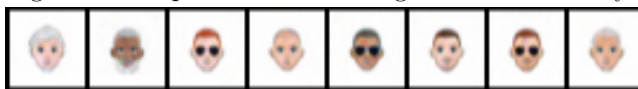


Figure 9: Samples of animation images in cartoon style

- iii. Briefly describe what is mode collapse. According to (ii), is mode collapse issue serious in this task? Why?

Hints

- a. Training procedure of GANs is unstable. When visualizing the loss curve, you can do moving average every N steps to smooth the curve and to observe the trend easily.
- b. You can decide the number of [deconvolution](#)/[convolution](#) layers in [generator](#)/[discriminator](#) by yourself.
- c. Optimizer such as [Adam](#) or [RMSProp](#) is recommended. If you use SGD, it may take more iterations to converge.
- d. You may set different learning rate for G and D . Usually, learning rate of D could be smaller than G .
- e. If you don't have much time or a powerful GPU, we suggest you to use smaller size of images (such as 32x32) and fewer epochs.
- f. Batch normalization is useful for training neural network.