# CS 2770 Assignment 4: Generative Models

## Introduction

In this assignment, you will get hands-on experience coding and training GANs. This assignment includes two parts: in the first part, we will implement a specific type of GAN designed to process images, called a Deep Convolutional GAN (DCGAN). We will train the DCGAN to generate grumpy cats from samples of random noise. In the second part, we will implement a more complex GAN architecture called CycleGAN for the task of image-to-image translation (described in more detail in Part 2). We will train the CycleGAN to convert between different types of two kinds of cats (Grumpy and Russian Blue). In both parts, you will gain experience implementing GANs by writing code for the generator, discriminator, and training loop, for each model. Code and data are available in A4 Github Repo.

## Part 1: Deep Convolutional GAN

For the first part of this assignment, we will implement a slightly modified version of Deep Convolutional GAN (DCGAN). A DCGAN is simply a GAN that uses a convolutional neural network as the discriminator, and a network composed of transposed convolutions as the generator. In the assignment, instead of using transposed convolutions, we will be using a combination of a upsampling layer and a convolution layer to replace transposed convolutions. To implement the DCGAN, we need to specify three things: 1) the generator, 2) the discriminator, and 3) the training procedure. We will develop each of these three components in the following subsections.

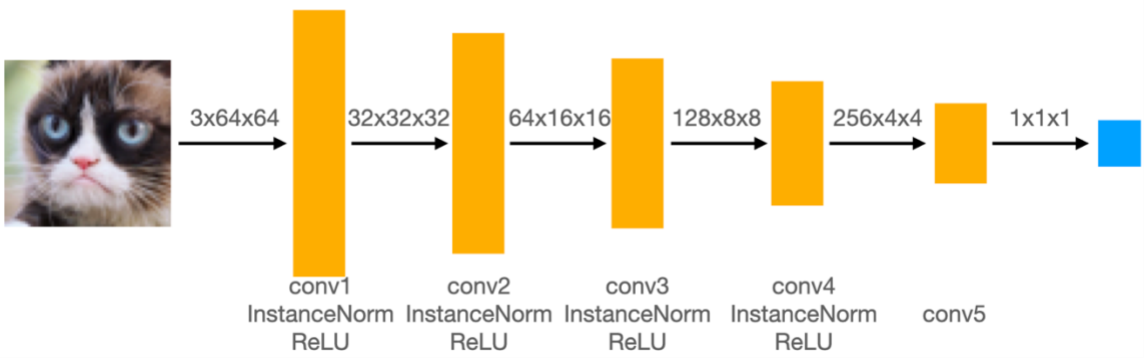
### *Implement Data Augmentation*

DCGAN will perform poorly without data augmentation on a small-sized dataset because the discriminator can easily overfit to a real dataset. To rescue, we need to add some data augmentation such as random crop and random horizontal flip. You need to fill in deluxe version of data augmentation in `data_loader.py`. We provide some script for you to begin with. You need to compose them into a transform object which is passed to CustomDataset.

```
elif opts.data_preprocess == 'deluxe':
    # add addtional data augmentation here
    # load_size = int(1.1 * opts.image_size)
    # osize = [load_size, load_size]
    # transforms.Resize(osize, Image.BICUBIC)
    # transforms.RandomCrop(opts.image_size)
    # transforms.RandomHorizontalFlip()
    pass
```

***Implement the Discriminator of the DCGAN*** **[10 pts]**

The discriminator in this DCGAN is a convolutional neural network with the following architecture:




1. **Padding**: In each of the convolutional layers shown above, we downsample the spatial dimension of the input volume by a factor of 2. Given that we use kernel size K = 4 and stride S = 2, what should the padding be? Write your answer on your writeup, and show your work (e.g., the formula you used to derive the padding).
2. **Implementation**: Implement this architecture by filling in the `__init__` and `forward` method of the `DCDiscriminator` class in `models.py`, shown below. The `conv_dim` argument does not need to be changed unless you are using larger images, as it should specify the initial image size.

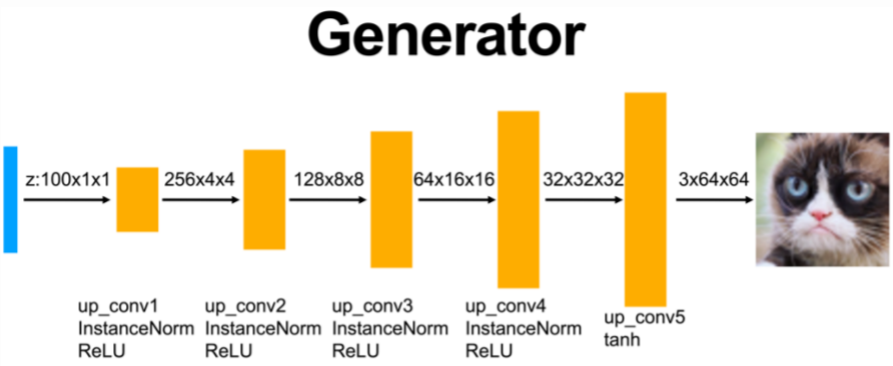
```
def __init__(self, conv_dim=64):
      super(DCDiscriminator, self).__init__()
      ########################################
      ##   FILL THIS IN: CREATE ARCHITECTURE   ##
      ########################################
      # self.conv1 = conv(...)
      # self.conv2 = conv(...)
      # self.conv3 = conv(...)
      # self.conv4 = conv(...)
      # self.conv5 = conv(...)
```

```
def forward(self, x):
    """Outputs the discriminator score given an image.

        Input
        -----
            x: BS x 3 x 64 x 64

        Output
        ------
            out: BS x 1 x 1 x 1
    """
    ##########################################
    ##   FILL THIS IN: FORWARD PASS   ##
    ##########################################
    pass
```

**Note**: The function `conv` in `models.py` has an optional argument `norm`: if `norm` is `none`, then `conv` simply returns a `torch.nn.Conv2d` layer; if `norm` is `instance/batch`, then `conv` returns a network block that consists of a `Conv2d` layer followed by a `torch.nn.InstanceNorm2d/BatchNorm2d` layer. Use the `conv` function in your implementation.

### *Generator* [10 pts]

Now, we will implement the generator of the DCGAN, which consists of a sequence of upsample+convolutional layers that progressively upsample the input noise sample to generate a fake image. The generator in this DCGAN has the following architecture:




1. **Implementation**: Implement this architecture by filling in the `__init__` and `forward` method of the `DCGenerator` class in `models.py`. **Note**: Use the `up_conv` function (analogous to the `conv` function used for the discriminator above) in your generator implementation. **We find that for the first layer (`up_conv1`) it is better to directly apply convolution layer without any upsampling to get 4x4 output. To do so, you'll need to think about what you kernel**

**and padding size should be in this case. Feel free to us `up_conv` for the rest of the layers.**

### *Training Loop* [10 pts]

Next, you will implement the training loop for the DCGAN. A DCGAN is simply a GAN with a specific type of generator and discriminator; thus, we train it in exactly the same way as a standard GAN. The pseudo-code for the training procedure is shown below. The actual implementation is simpler than it may seem from the pseudo-code: this will give you practice in translating math to code.

1. **Implementation**: Open up the file `vanilla_gan.py` and fill in the indicated parts of the `training_loop` function, starting at the line where it says:

```
# FILL THIS IN
# 1. Compute the discriminator loss on real images # D_real_loss = ...
```

There are 5 numbered bullets in the code to fill in for the discriminator and 3 bullets for the generator. Each of these can be done in a single line of code, although you will not lose marks for using multiple lines.

**Algorithm 1** GAN Training Loop Pseudocode

**procedure** TRAINGAN

Draw $m$ training examples $\{x^{(1)}, \ldots, x^{(m)}\}$ from the data distribution $p_{data}$

**Draw $m$ noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from the noise distribution $p_z$**

**Generate fake images from the noise: $G(z^{(i)})$ for $i \in \{1, \ldots m\}$**

**Compute the (least-squares) discriminator loss:**

$$J^{(D)} = \frac{1}{2m}\sum_{i=1}^{m}\left[\left(D(x^{(i)}) - 1\right)^2\right] + \frac{1}{2m}\sum_{i=1}^{m}\left[\left(D(G(z^{(i)}))\right)^2\right]$$

Update the parameters of the discriminator

**Draw $m$ new noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from the noise distribution $p_z$**

**Generate fake images from the noise: $G(z^{(i)})$ for $i \in \{1, \ldots m\}$**

**Compute the (least-squares) generator loss:**

$$J^{(G)} = \frac{1}{m}\sum_{i=1}^{m}\left[\left(D(G(z^{(i)})) - 1\right)^2\right]$$

Update the parameters of the generator

### *Differentiable Augmentation*

To further improve the data efficiency of GANs, one can apply differentiable augmentations discussed in this paper. Similar to the previous data augmentation scheme, the idea is to reduce overfitting in the discriminators by applying augmentation, but this time we apply augmentation to both the real and fake images during training time. The differentiable augmentation code is provided in the file `diff_augment.py`, and you will be applying the code to DCGAN training. **In the write up, please show results with and without applying differentiable augmentations, and**

**discuss the difference between two augmentation schemes, in terms of implementation and effects.**

***Experiment with DCGANs [20 points]***

1. Train the DCGAN with the command:

```
python vanilla_gan.py
```

The script saves the output of the generator for a fixed noise sample every 200 iterations throughout training; this allows you to see how the generator improves over time. **Include the following in your writeup**:

- Screenshots of discriminator and generator training loss with `--data_preprocess=basic`, `--data_preprocess=deluxe`. For each `--data_preprocess` flag, also show results trained both with and without differentiable augmentation, so you will show 8 curves in total. Briefly explain what the curves should look like if GAN manages to train.
- With `--data_preprocess=deluxe` and differentiable augmentation enabled, show one of the samples from early in training (e.g., iteration 200) and one of the samples from later in training, and give the iteration number for those samples. Briefly comment on the quality of the samples, and in what way they improve through training.

Below, I generate a sample with `--data_preprocess=deluxe` and differentiable augmentation. Please, use it as reference for debugging purposes.

**Part 2: CycleGAN**

Now we are going to implement the CycleGAN architecture.

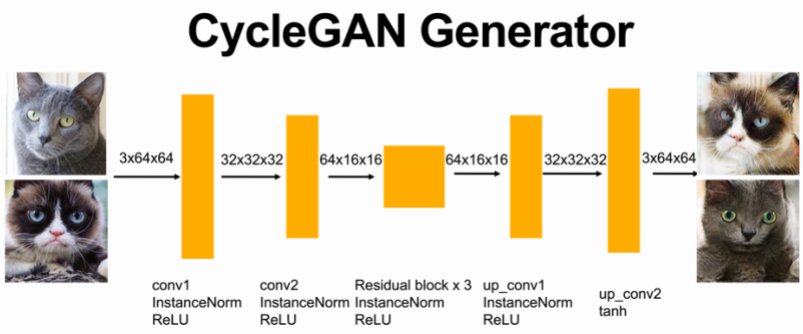
***Data Augmentation***

Remember to set the `--data_preprocess` flag to deluxe or feel free to add differentiable augmentation or your additional data augmentation. Please, mention in your **writeup** your choices.

## *Generator* [10 pts]

The generator in the CycleGAN has layers that implement three stages of computation: 1) the first stage *encodes* the input via a series of convolutional layers that extract the image features; 2) the second stage then *transforms* the features by passing them through one or more residual blocks; and 3) the third stage *decodes* the transformed features using a series of transposed convolutional layers, to build an output image of the same size as the input. The residual block used in the transformation stage consists of a convolutional layer, where the input is added to the output of the convolution. This is done so that the characteristics of the output image (e.g., the shapes of objects) do not differ too much from the input. Implement the following generator architecture by completing the `__init__` method of the `CycleGenerator` class in `models.py`.

```
def __init__(self, conv_dim=64, init_zero_weights=False):
     super(CycleGenerator, self).__init__()
    ##########################################
    # 1. Define the encoder part of the generator
    # self.conv1 = ...
    # self.conv2 = ...
    # 2. Define the transformation part of the generator
    # self.resnet_block = ...
    # 3. Define the decoder part of the generator
    # self.up_conv1 = ...
    # self.up_conv2 = ...
```




To do this, you will need to use the `conv` and `up_conv` functions, as well as the `ResnetBlock` class, all provided in `models.py`. **Note:** There are two generators in the `CycleGAN` model, $G_{X\to Y}$ and $G_{Y\to X}$, but their implementations are identical. Thus, in the code, $G_{X\to Y}$ and $G_{Y\to X}$ are simply different instantiations of the same class.

### *PatchDiscriminator* [5 pts]

CycleGAN adopts a patch-based discriminator. Instead of directly classifying an image to be real or fake, it classifies the patches of the images, allowing CycleGAN to model local structures better. To achieve this effect, you will want the discriminator to produce spatial outputs (e.g., 4x4) instead of a scalar (1x1). We ask you to implement this discriminator architecture by completing the `PatchDiscriminator` class in `models.py`. It turns out this can be done by slightly modifying the `DCDiscriminator` class. (*Hint: You can implement a PatchDiscriminator by removing a layer from the DCDiscriminator.*)

### *CycleGAN Training Loop* [10 pts]

Finally, we will implement the CycleGAN training procedure, which is more involved than the procedure in Part 1.

**Algorithm 2** CycleGAN Training Loop Pseudocode

**procedure** TRAINCYCLEGAN

Draw a minibatch of samples $\{x^{(1)}, \ldots, x^{(m)}\}$ from domain $X$

Draw a minibatch of samples $\{y^{(1)}, \ldots, y^{(m)}\}$ from domain $Y$

Compute the discriminator loss on real images:

$$\mathcal{J}_{real}^{(D)} = \frac{1}{m}\sum_{i=1}^{m}(D_X(x^{(i)}) - 1)^2 + \frac{1}{n}\sum_{j=1}^{n}(D_Y(y^{(j)} - 1)^2$$

Compute the discriminator loss on fake images:

$$\mathcal{J}_{fake}^{(D)} = \frac{1}{m}\sum_{i=1}^{m}(D_Y(G_{X\to Y}(x^{(i)})))^2 + \frac{1}{n}\sum_{j=1}^{n}(D_X(G_{Y\to X}(y^{(j)})))^2$$

Update the discriminators

Compute the $Y \to X$ generator loss:

$$\mathcal{J}^{(G_{Y\to X})} = \frac{1}{n}\sum_{j=1}^{n}(D_X(G_{Y\to X}(y^{(j)})) - 1)^2 + \mathcal{J}_{cycle}^{(Y\to X\to Y)}$$

Compute the $X \to Y$ generator loss:

$$\mathcal{J}^{(G_{X\to Y})} = \frac{1}{m}\sum_{i=1}^{m}(D_Y(G_{X\to Y}(x^{(i)})) - 1)^2 + \mathcal{J}_{cycle}^{(X\to Y\to X)}$$

Update the generators

Similarly to Part 1, this training loop is not as difficult to implement as it may seem. There is a lot of symmetry in the training procedure, because all operations are done for both X → Y and Y → X directions. Complete the `training_loop` function in `cycle_gan.py`, starting from the following section:

```
# ========================================
#           TRAIN THE DISCRIMINATORS
# ========================================
########################################
##            FILL THIS IN            ##
########################################

# 1. Compute the discriminator losses on real images
# D_X_loss = ...
# D_Y_loss = ...
```

There are 5 bullet points in the code for training the discriminators, and 6 bullet points in total for training the generators. Due to the symmetry between domains, several parts of the code you fill in will be identical except for swapping X and Y; this is normal and expected.

### *Cycle Consistency* [5 pts]

The most interesting idea behind CycleGANs (and the one from which they get their name) is the idea of introducing a cycle consistency loss to constrain the model. The idea is that when we translate an image from domain **X** to domain **Y**, and then translate the generated image back to domain **X**, the result should look like the original image that we started with. The cycle consistency component of the loss is the mean squared error between the input images and their reconstructions obtained by passing through both generators in sequence (i.e., from domain **X** to **Y** via the **X → Y** generator, and then from domain **Y** back to **X** via the **Y → X** generator). The cycle consistency loss for the **Y → X → Y** cycle is expressed as follows:

$$\frac{1}{m}\sum_{i=1}^{m} ||y^{(i)} - G_{X\to Y}(G_{Y\to X}(y^{(i)}))||_p$$

The loss for the **X → Y → X** cycle is analogous. Here the traditional choice of **p** is 1 but you can try 2 as well if you vary your $\lambda_{cycle}$. Implement the cycle consistency loss by filling in the following section in `cycle_gan.py`. Note that there are two such sections, and their implementations are identical except for swapping **X** and **Y**. You must implement both of them.

```
if opts.use_cycle_consistency_loss:
    # 3. Compute the cycle consistency loss (the reconstruction loss)
    # cycle_consistency_loss = ...
    g_loss += cycle_consistency_loss
```

### *CycleGAN Experiments [20 points]*

Training the CycleGAN from scratch can be time-consuming if you do not have a GPU. In this part, you will train your models from scratch for just 1000 iterations, to check the results.

1. Train the CycleGAN without the cycle-consistency loss from scratch using the command:

```
python cycle_gan.py --disc patch --train_iters 1000
```

This runs for 1000 iterations, and saves generated samples in the `output/cyclegan` folder. In each sample, images from the source domain are shown with their translations to the right. Include in your writeup the samples from both generators at either iteration 800 or 1000, e.g., `sample-001000-X-Y.png` and `sample-001000-Y-X.png`. Train the CycleGAN with the cycle-consistency loss from scratch using the command:

```
python cycle_gan.py --disc patch --use_cycle_consistency_loss  --train_iters 1000
```

Similarly, this runs for 1000 iterations, and saves generated samples in the `output/cyclegan` folder. Include in your writeup the samples from both generators at either iteration 800 or 1000 as above. Please, observe my results as reference for debugging.

2. If the previous looks reasonable, it is time to train longer time. Please show results after training 10000 iterations. **Include the sampled output from your model.**
3. Do you notice a difference between the results with and without the cycle consistency loss? Write down your observations (positive or negative) in your

writeup. Can you explain these results, i.e., why there is or isn't a difference between the two?

4. Train the CycleGAN with the `DCDiscriminator` for comparison:

```
python cycle_gan.py --disc dc --use_cycle_consistency_loss
```

Compare and report your observations between the results using `DCDiscriminator` and `PatchDiscriminator`. Can you explain the results?

Perform the comparisons of 3 and 4 on both the `grumpifyCat` dataset.

**What you need to modify for submission**

- Four code files: `models.py`, `vanilla_gan.py`, `data_loader.py` and `cycle_gan.py`.
- A **writeup** file `A04_report.pdf` containing samples generated by your DCGAN and CycleGAN models, and your answers to the written questions as specified in the previous sections.

**Further Resources**

- Generative Adversarial Nets (Goodfellow et al., 2014)
- Generative Models Blog Post from OpenAI
- Unpaired image-to-image translation using cycle-consistent adversarial networks (Zhu et al., 2017)
- Official PyTorch Implementations of Pix2Pix and CycleGAN

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