part1

April 30, 2024

1 CS 5814 Homework 4, Part 1: Generative Adversarial Networks

[1]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

[1]:
```
import os
# os.chdir("/content/drive/MyDrive/Colab Notebooks/Intro to DL Course/HW4/hw4/part1")
path = os.getcwd()
path
```

[1]:
```
'/home/nima/RAMIN/HW4/Part1'
```

[2]:
```
import torch
from torch.utils.data import DataLoader
from torchvision import transforms
from torchvision.datasets import ImageFolder
import matplotlib.pyplot as plt
import numpy as np

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

%load_ext autoreload
%autoreload 2
```

[3]:
```
from gan.train import train
```

[4]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

[5]:
```
device
```

[5]:
```
device(type='cuda', index=0)
```

2 GAN loss functions

You'll need to implement two different loss functions. The first is the loss from the original GAN paper. The next is the loss from LS-GAN.

2.0.1 GAN loss

TODO: You need to implement the `discriminator_loss` and `generator_loss` functions in `gan/losses.py`.

The generator loss is given by:

$$\ell_G = -\mathbb{E}_{z\sim p(z)}\left[\log D(G(z))\right]$$

and the discriminator loss is:

$$\ell_D = -\mathbb{E}_{x\sim p_{\text{data}}}\left[\log D(x)\right] - \mathbb{E}_{z\sim p(z)}\left[\log\left(1 - D(G(z))\right)\right]$$

Note that these equations are negated because we will be *minimizing* these losses.

HINTS: Use the `torch.nn.functional.binary_cross_entropy_with_logits` function to compute the binary cross entropy loss since it is more numerically stable than using a softmax followed by BCE loss.

We will be averaging over the elements of the minibatch instead of computing the expectation of $\log D(G(z))$, $\log D(x)$ and $\log\left(1 - D(G(z))\right)$.

[6]:
```
from gan.losses import discriminator_loss, generator_loss
```

2.0.2 Least Squares GAN loss

TODO: You need to implement the `ls_discriminator_loss` and `ls_generator_loss` functions in `gan/losses.py`.

Least Squares GAN is an alernative to the original GAN loss function. For this part, all you need to do change the loss function and retrain the model.

Specifically, you'll implement equation (9) in the paper:

$$\ell_G = \frac{1}{2}\mathbb{E}_{z\sim p(z)}\left[\left(D(G(z)) - 1\right)^2\right]$$

and the discriminator loss:

$$\ell_D = \frac{1}{2}\mathbb{E}_{x\sim p_{\text{data}}}\left[\left(D(x) - 1\right)^2\right] + \frac{1}{2}\mathbb{E}_{z\sim p(z)}\left[\left(D(G(z))\right)^2\right]$$

[7]:
```
from gan.losses import ls_discriminator_loss, ls_generator_loss
```

3 GAN model architecture

TODO: Next, you'll need to implement the `Discriminator` and `Generator` networks in `gan/models.py`.

We'll be using the architecture from DCGAN:

Discriminator:

- convolutional layer with in_channels=3, out_channels=128, kernel=4, stride=2
- convolutional layer with in_channels=128, out_channels=256, kernel=4, stride=2
- batch norm
- convolutional layer with in_channels=256, out_channels=512, kernel=4, stride=2
- batch norm
- convolutional layer with in_channels=512, out_channels=1024, kernel=4, stride=2
- batch norm
- convolutional layer with in_channels=1024, out_channels=1, kernel=4, stride=1

Use padding = 1 (not 0) for all the convolutional layers.

You can either use LeakyReLu throughout the discriminator (and a negative slope value of 0.2) or just use relu.

The discriminator will output a single score for each sample.The output of your discriminator should be a single value score corresponding to each input sample.

Generator:

Note: Here, you'll need to use transposed convolution (sometimes known as fractionally-strided convolution). This function is implemented in pytorch as `torch.nn.ConvTranspose2d`.

- transpose convolution with in_channels=NOISE_DIM, out_channels=1024, kernel=4, stride=1
- batch norm
- transpose convolution with in_channels=1024, out_channels=512, kernel=4, stride=2
- batch norm
- transpose convolution with in_channels=512, out_channels=256, kernel=4, stride=2
- batch norm
- transpose convolution with in_channels=256, out_channels=128, kernel=4, stride=2
- batch norm
- transpose convolution with in_channels=128, out_channels=3, kernel=4, stride=2

The generator network will need to map the output values between -1 and 1 using a `tanh` nonlinearity. The output should be of size 64x64 with 3 channels for each sample (equal dimensions to the images from the dataset).

[8]:
```
from gan.models import Discriminator, Generator
```

4 Data loading

Our dataset is pretty small, so in order to prevent overfitting, we need to perform data augmentation.

TODO: You'll need to implement some data augmentation by adding new transforms to the cell below.

The easiest you can do is just use the RandomCrop and ColorJitter, but feel free to play around with other augmentations as well to see how it affects the performance of your model. See https://pytorch.org/vision/stable/transforms.html.

[9]:
```
# # Define the transform for the training data.
# transform = transforms.Compose([
#     transforms.RandomResizedCrop(64, scale=(0.8, 1.0), ratio=(0.95, 1.05)),
 ↪# Randomly crop and resize the image to 64x64.
#     transforms.RandomHorizontalFlip(),  # Randomly flip the image
 ↪horizontally.
#     transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1),  #
 ↪Randomly change the brightness, contrast, and saturation of the image.
#     transforms.ToTensor(),  # Convert the image to a PyTorch tensor.
#     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),  # Normalize the
 ↪image.
# ])
```

[10]:
```
print(os.path.exists('./cats'))  # This should return True if the directory
 ↪exists
```

```
True
```

[11]:
```
!ls
```

```
cats  cats.zip  gan  part1.ipynb  part1.pdf
```

[12]:
```
batch_size = 32
imsize = 64
cat_root = './cats'

cat_train = ImageFolder(root=cat_root, transform=transforms.Compose([
  transforms.ToTensor(),
  transforms.RandomResizedCrop(64, scale=(0.8, 1.0), ratio=(0.95, 1.05)),  #
 ↪Randomly crop and resize the image to 64x64.
  transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1),  #
 ↪Randomly change the brightness, contrast, and saturation of the image.
  # transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),  # Normalize the
 ↪image.

    ## Use some some augmentations here

]))

cat_loader_train = DataLoader(cat_train, batch_size=batch_size, drop_last=True)
```

[13]:
```
len(cat_train)
```

[13]: 15747

4.0.1 Visualize dataset

[14]:
```
from gan.utils import show_images

# imgs = cat_loader_train.__iter__().next()[0].numpy().squeeze()
imgs = next(iter(cat_loader_train))[0].numpy().squeeze()
show_images(imgs, color=True)
```

5 Training

TODO: You need to write the training loop in `gan/train.py`.

[15]:
```
NOISE_DIM = 100
NUM_EPOCHS = 20
learning_rate = 0.001
```

5.0.1 Train GAN

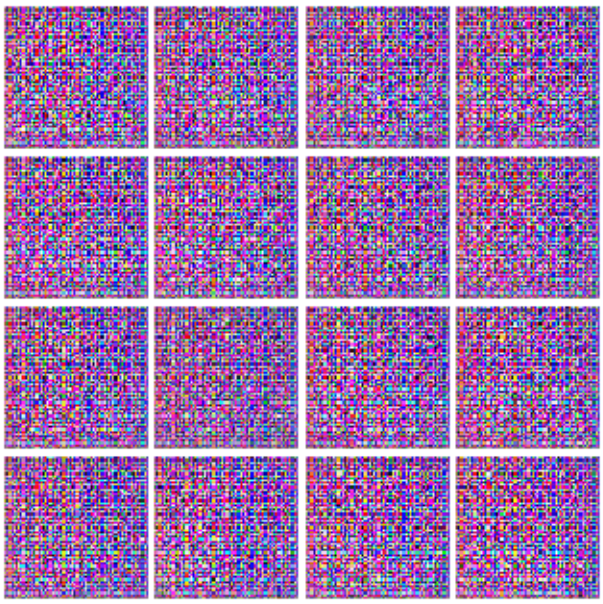
[16]:
```
D = Discriminator().to(device)
G = Generator(noise_dim=NOISE_DIM).to(device)
```

[17]:
```
D_optimizer = torch.optim.Adam(D.parameters(), lr=learning_rate, betas = (0.5,␣
↪0.999))
G_optimizer = torch.optim.Adam(G.parameters(), lr=learning_rate, betas = (0.5,␣
↪0.999))
```

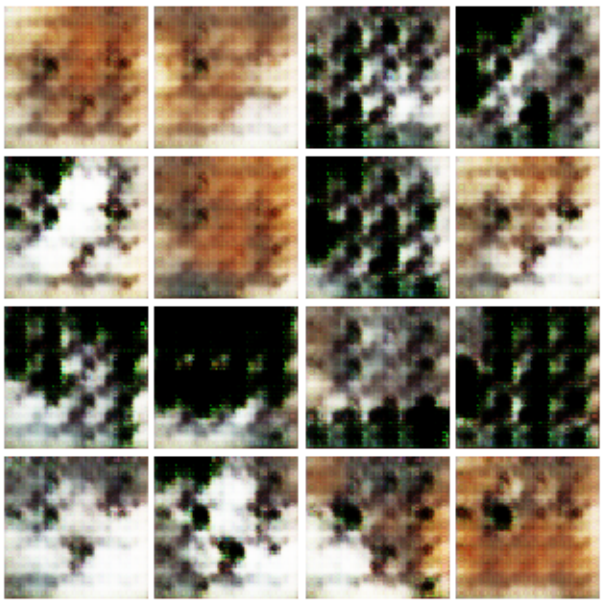
[18]:
```
from gan.train import train
```

[19]:
```
# original gan
train(D, G, D_optimizer, G_optimizer, discriminator_loss,
          generator_loss, num_epochs=NUM_EPOCHS, show_every=250,
          batch_size=batch_size, train_loader=cat_loader_train, device=device)
```

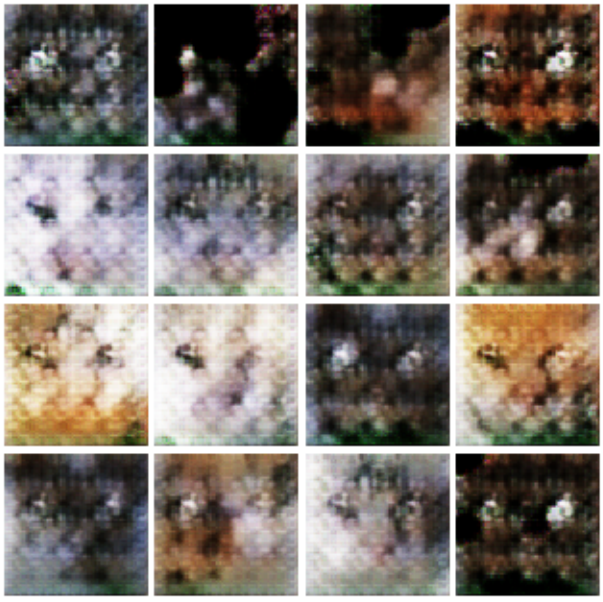
```
EPOCH:  1
Iter: 0, D: 0.7127, G:4.19
```



```
EPOCH:  2
Iter: 500, D: 0.9389, G:1.018
```

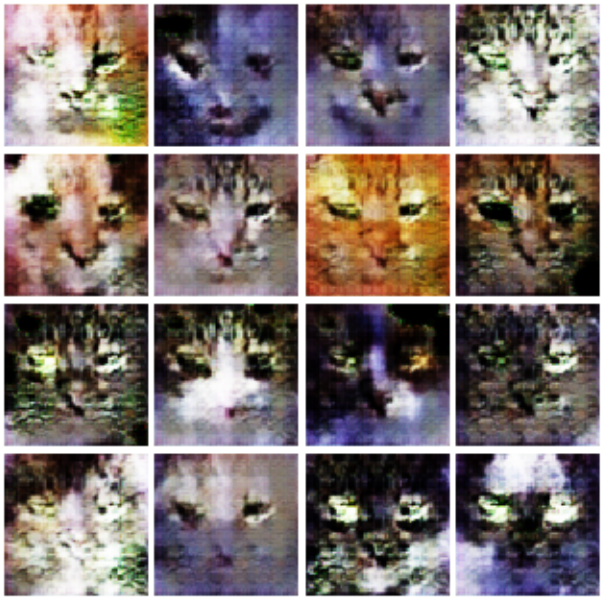


EPOCH: 3
Iter: 1000, D: 0.3405, G:2.709



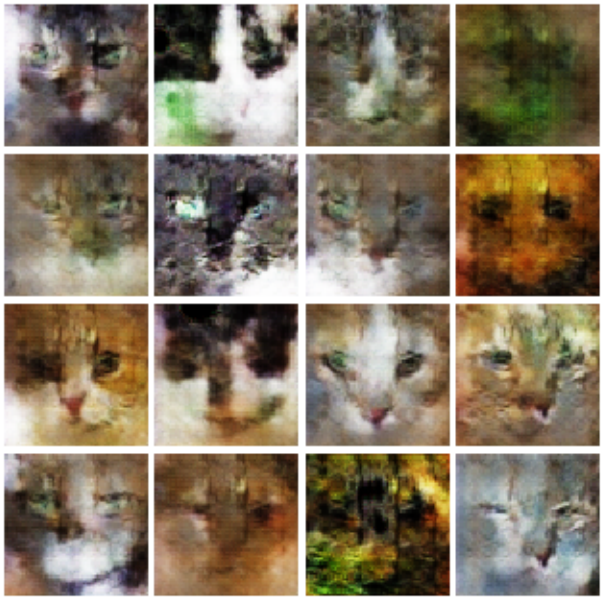
EPOCH: 4
Iter: 1500, D: 0.4914, G:2.447

EPOCH: 5
Iter: 2000, D: 0.6272, G:2.936



EPOCH: 6
Iter: 2500, D: 0.3728, G:2.41

EPOCH: 7
Iter: 3000, D: 0.4909, G:3.953



EPOCH: 8
Iter: 3500, D: 0.3892, G:1.244

EPOCH: 9
Iter: 4000, D: 0.3003, G:3.692

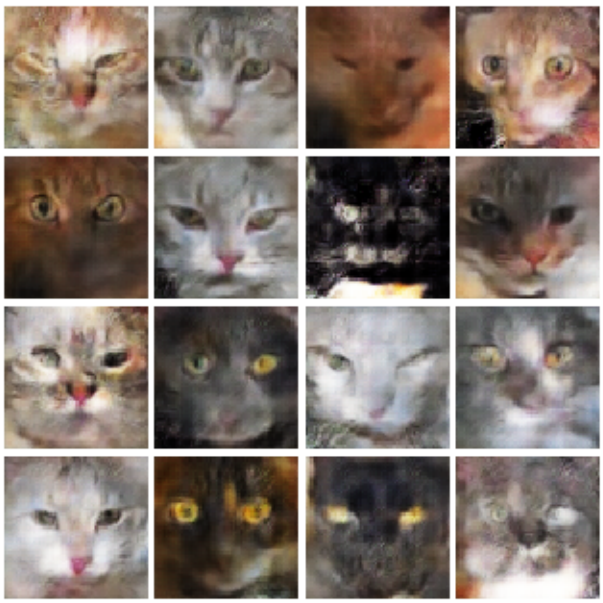
EPOCH: 10
Iter: 4500, D: 0.382, G:4.164

EPOCH: 11
Iter: 5000, D: 0.6974, G:7.925

EPOCH: 12
Iter: 5500, D: 0.06653, G:6.629

EPOCH: 13
Iter: 6000, D: 0.1146, G:3.97

EPOCH: 14
Iter: 6500, D: 0.1337, G:5.532

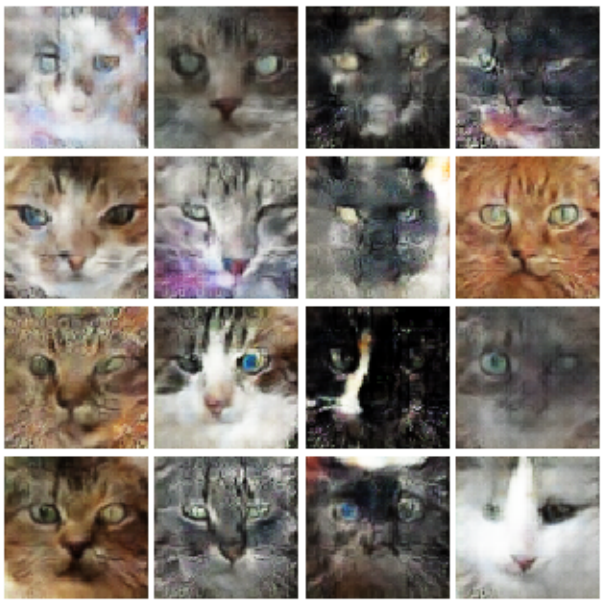


EPOCH: 15
Iter: 7000, D: 0.04765, G:5.568

EPOCH: 16
Iter: 7500, D: 0.06044, G:5.518

EPOCH: 17
Iter: 8000, D: 0.04569, G:3.245

EPOCH: 18
Iter: 8500, D: 0.5909, G:8.673



```
EPOCH:  19
Iter: 9000, D: 0.06816, G:4.749
```

```
EPOCH:  20
Iter: 9500, D: 0.1145, G:6.261
```

5.0.2 Train LS-GAN

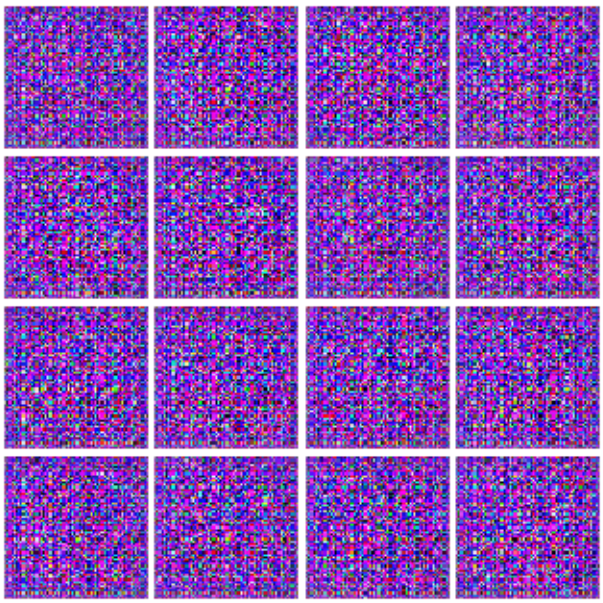
[21]:
```
NOISE_DIM = 100
NUM_EPOCHS = 20
learning_rate = 0.001
```

[25]:
```
D = Discriminator().to(device)
G = Generator(noise_dim=NOISE_DIM).to(device)
```

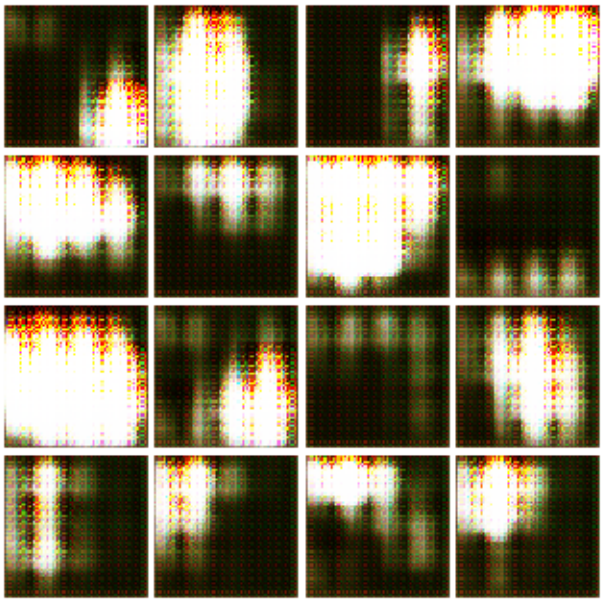
[26]:
```
D_optimizer = torch.optim.Adam(D.parameters(), lr=learning_rate, betas = (0.5,␣
↪0.999))
G_optimizer = torch.optim.Adam(G.parameters(), lr=learning_rate, betas = (0.5,␣
↪0.999))
```

[27]:
```
# ls-gan
train(D, G, D_optimizer, G_optimizer, ls_discriminator_loss,
          ls_generator_loss, num_epochs=NUM_EPOCHS, show_every=250,
          batch_size=batch_size, train_loader=cat_loader_train, device=device)
```

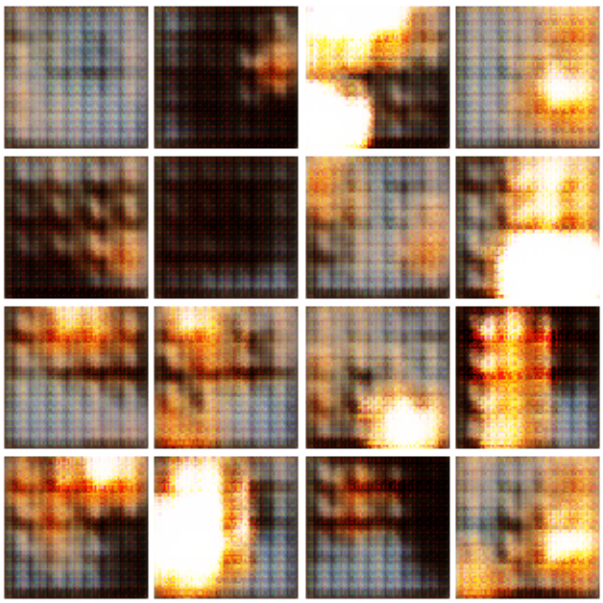
```
EPOCH:  1
Iter: 0, D: 0.2604, G:0.9795
```



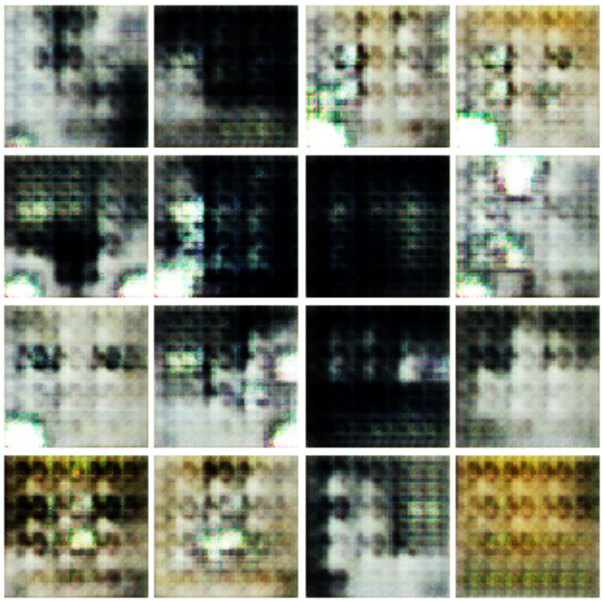
```
Iter: 250, D: 0.003747, G:0.9884
```



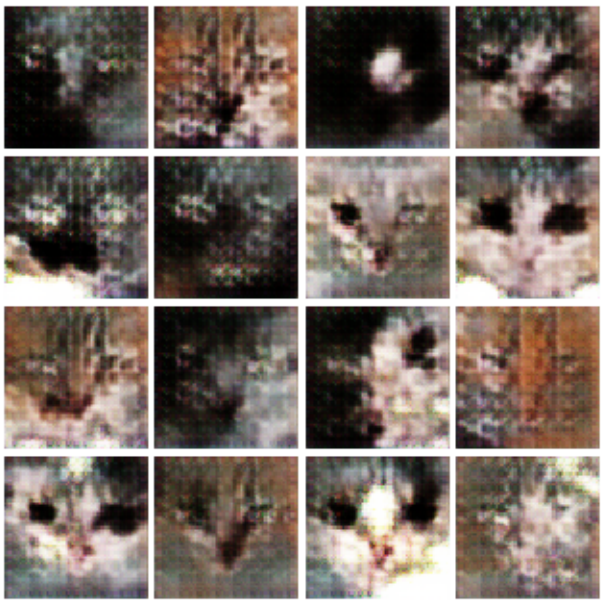
```
EPOCH:  2
Iter: 500, D: 0.3438, G:0.7185
```



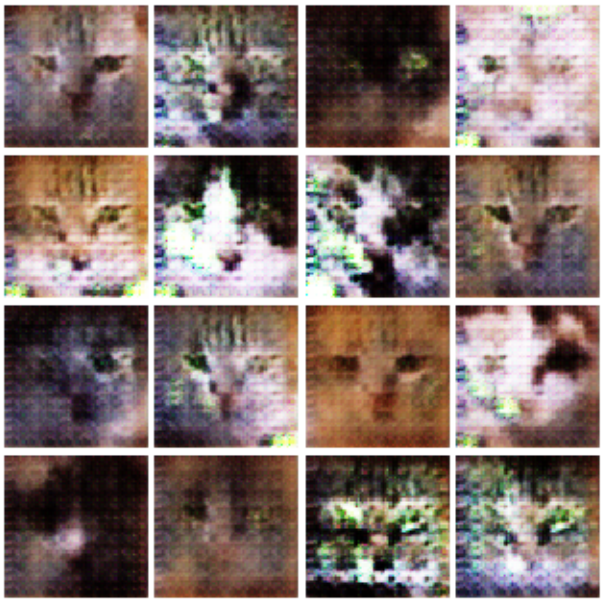
```
Iter: 750, D: 0.3125, G:0.4301
```



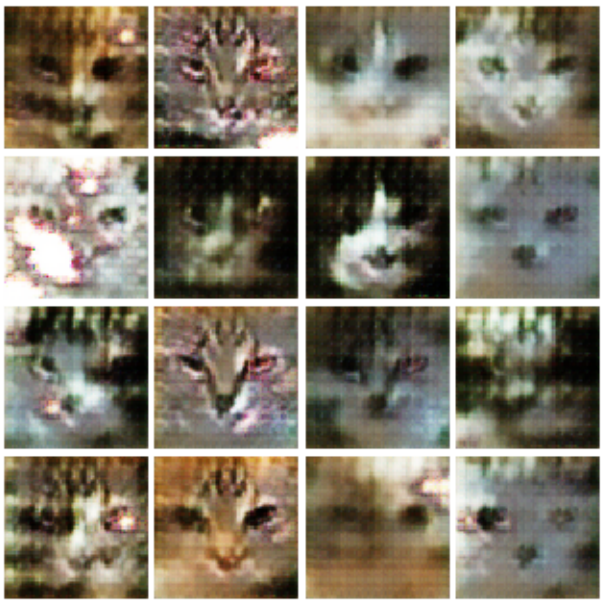
```
EPOCH:  3
Iter: 1000, D: 0.195, G:0.7984
```



Iter: 1250, D: 0.2617, G:0.6795

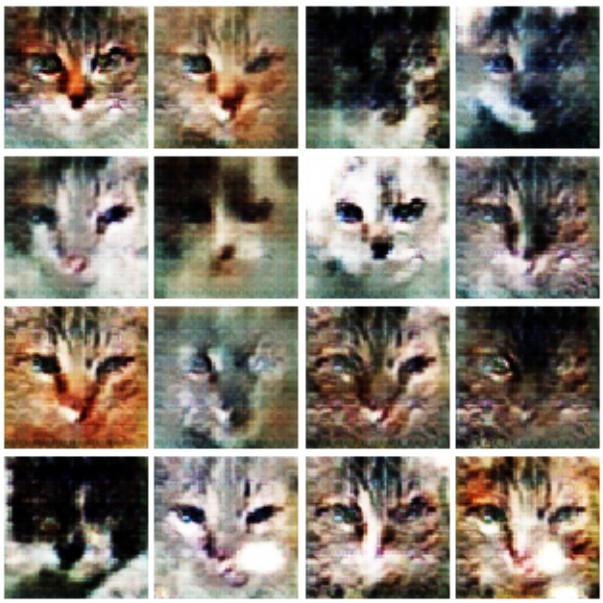


EPOCH: 4
Iter: 1500, D: 0.1192, G:0.8129



```
Iter: 1750, D: 0.1228, G:0.8671
```

```
EPOCH:  5
Iter: 2000, D: 0.1786, G:0.6939
```

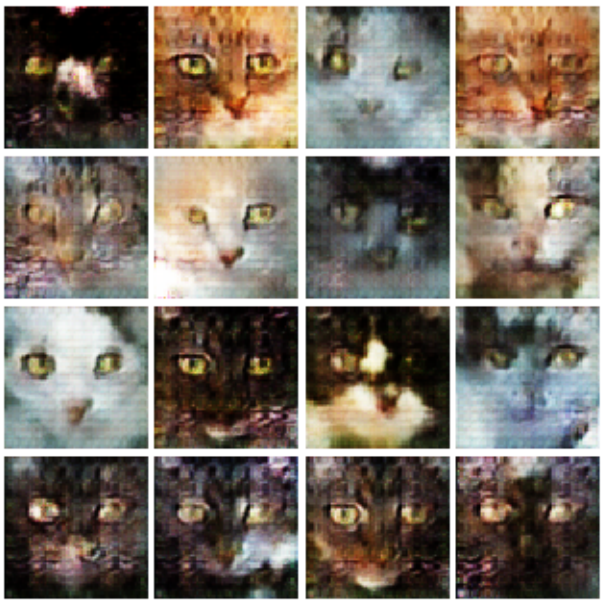


```
Iter: 2250, D: 0.09538, G:0.916
```

```
EPOCH:  6
Iter: 2500, D: 0.1319, G:0.8149
```

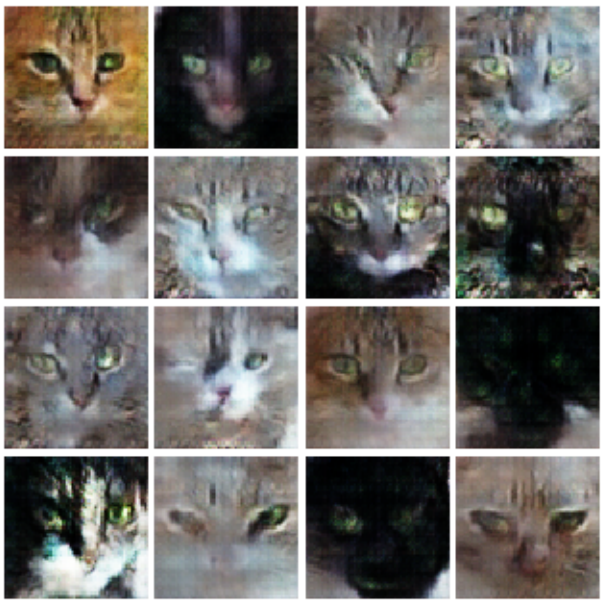
```
Iter: 2750, D: 0.1564, G:0.8501
```

```
EPOCH:  7
Iter: 3000, D: 0.1556, G:0.7582
```



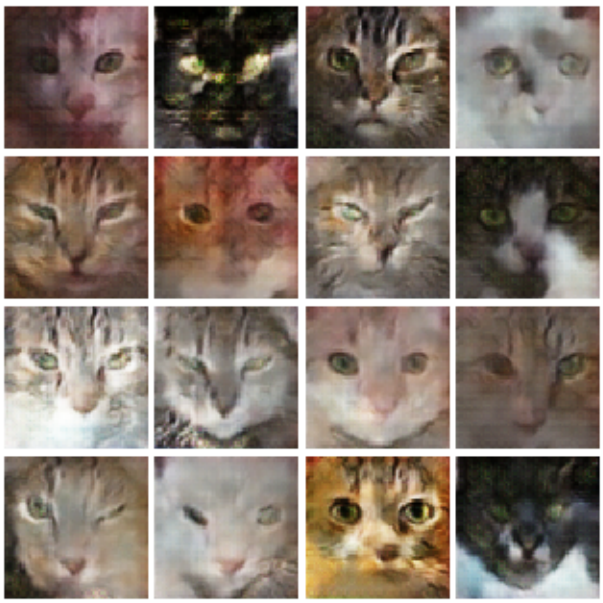
```
Iter: 3250, D: 0.1785, G:0.3048
```

```
EPOCH:  8
Iter: 3500, D: 0.1746, G:0.6137
```



```
Iter: 3750, D: 0.1475, G:0.6294
```

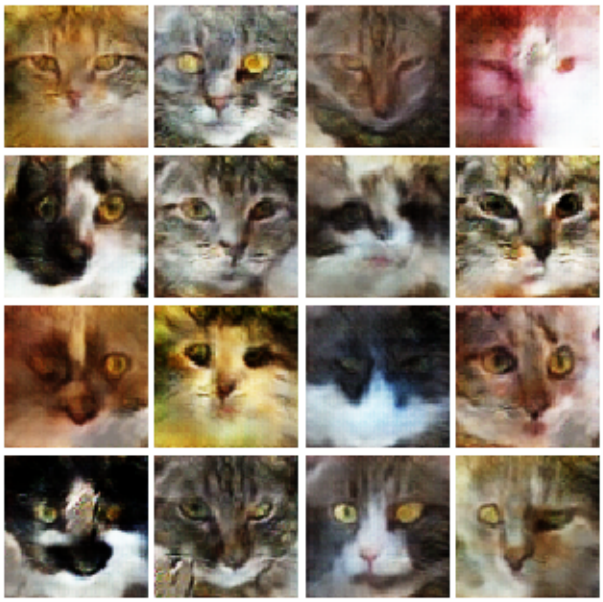
```
EPOCH:  9
Iter: 4000, D: 0.1261, G:0.7095
```



```
Iter: 4250, D: 0.1455, G:0.4997
```

```
EPOCH:  10
Iter: 4500, D: 0.1758, G:0.3328
```

```
Iter: 4750, D: 0.2195, G:0.6301
```



```
EPOCH:  11
Iter: 5000, D: 0.1994, G:0.5739
```

```
Iter: 5250, D: 0.1664, G:0.7533
```

```
EPOCH:  12
Iter: 5500, D: 0.1842, G:0.7227
```

```
Iter: 5750, D: 0.2389, G:0.603
```

```
EPOCH:  13
Iter: 6000, D: 0.1801, G:0.7105
```

```
Iter: 6250, D: 0.1662, G:0.4738
```

```
EPOCH:  14
Iter: 6500, D: 0.1508, G:0.5974
```

```
Iter: 6750, D: 0.1482, G:0.7407
```

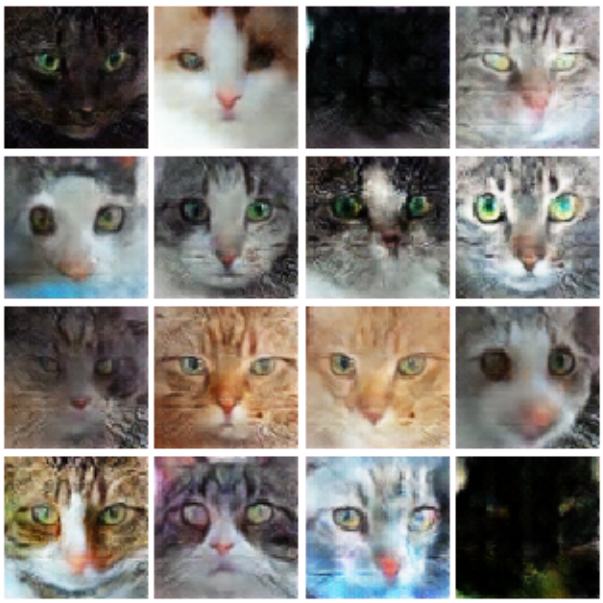
```
EPOCH:  15
Iter: 7000, D: 0.1864, G:0.4463
```

```
Iter: 7250, D: 0.1473, G:0.5582
```

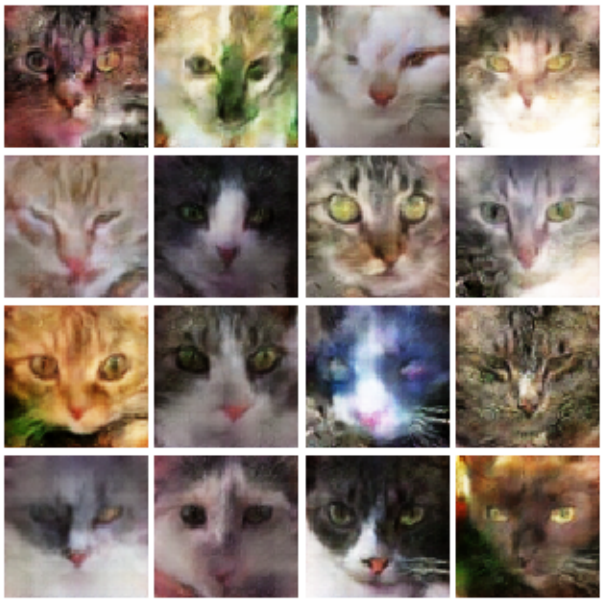
```
EPOCH:  16
Iter: 7500, D: 0.2664, G:0.7539
```

```
Iter: 7750, D: 0.1045, G:0.7488
```

```
EPOCH:  17
Iter: 8000, D: 0.1277, G:0.5346
```



```
Iter: 8250, D: 0.1305, G:0.7865
```



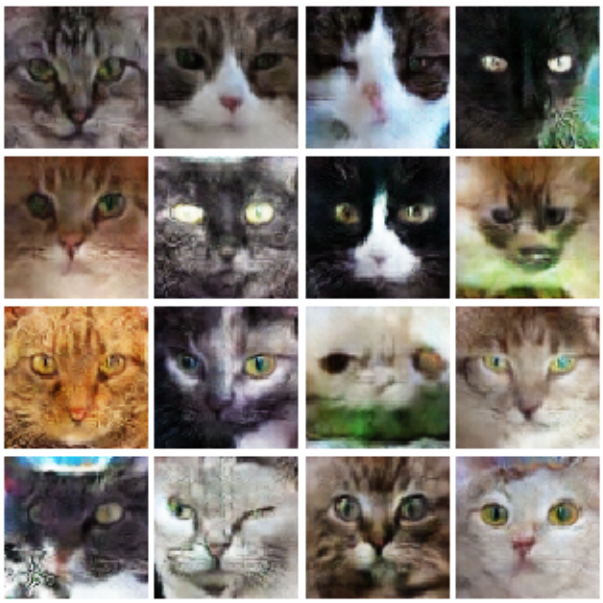
```
EPOCH:  18
Iter: 8500, D: 0.09923, G:0.7142
```

Iter: 8750, D: 0.1969, G:0.9193

EPOCH: 19
Iter: 9000, D: 0.01865, G:0.8821

Iter: 9250, D: 0.1067, G:0.4685

EPOCH: 20
Iter: 9500, D: 0.06706, G:0.6573



Iter: 9750, D: 0.1558, G:0.9762

[30]:
```
path = os.getcwd()
path
```

[30]:
```
'/home/nima/RAMIN/HW4/Part1'
```

[ ]:
```
# !pip install nbconvert
# !apt-get install texlive texlive-xetex texlive-latex-extra pandoc
# !pip install pypandoc

!jupyter nbconvert --to pdf "/home/nima/RAMIN/HW4/Part1/part1.ipynb"
```

```
[NbConvertApp] Converting notebook /home/nima/RAMIN/HW4/Part1/part1.ipynb to pdf
[NbConvertApp] Support files will be in part1_files/
[NbConvertApp] Making directory ./part1_files
[NbConvertApp] Writing 60826 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
```

[ ]:
```

```