Lab 4: Transfer Learning and GANs

Instructions

rubric={mechanics:5}

- Follow the general lab instructions
- Upload a PDF version of your lab notebook to Gradescope, in addition to the .ipynb file.
- Add a link to your GitHub repository here: https://github.ubc.ca/MDS-2022-23/DSCI_572_lab4_mengjun5

Imports

In [31]:
```
import numpy as np
import pandas as pd
from collections import OrderedDict
import torch
from torch import nn, optim
from torchvision import datasets, transforms, utils, models
import matplotlib.pyplot as plt
import matplotlib.animation as animation
from IPython.display import HTML
from PIL import Image
from statistics import mean


plt.rcParams.update({'axes.grid': False})
```

Getting Started with Kaggle

We are going to run this notebook on the cloud using Kaggle. Kaggle offers 30 hours of free GPU usage per week which should be much more than enough for this lab. To get started, follow these steps:

1. Go to https://www.kaggle.com/kernels
2. Make an account if you don't have one, and verify your phone number (to get access to GPUs)
3. Select `+ New Notebook`
4. Go to `File -> Import Notebook`
5. Upload this notebook
6. On the right-hand side of your Kaggle notebook, make sure:
    - `Internet` is enabled.

- In the `Accelerator` dropdown, choose one of the GPU options when you're ready to use it (you can turn it on/off as you need it).

Once you've done all your work on Kaggle, you can download the notebook from Kaggle. That way any work you did on Kaggle won't be lost.

Exercise 1: Transfer Learning

---

rubric={accuracy:15}

In this exercise you're going to practice transfer learning. We're going to develop a model that can detect the following 6 cat breeds in this Kaggle dataset:

1. American Short hair

2. Bengal

3. Maine Soon
4. Ragdoll
5. Scottish Fold
6. Sphinx

In order to use this dataset

1. Click `+ Add data` at the top right of the notebook.

2. Search for **"cat-breed"** and click `Add`

1.1: CNN from Scratch

In this exercise, you should build a CNN model to classify images of cats based on their breeds.

In Kaggle, running the follow cell should print out `"Using device: cuda"` which means a GPU is available:

In [27]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device.type}")
```

```
Using device: cpu
```

To make use of the GPU, you should:

1. Move your model to the GPU after creating it using this syntax:

```
model.to(device)
```

1. In your training/validation loops, each batch should be moved to the GPU using syntax like:

```
for X, y in dataloader:
    X, y = X.to(device), y.to(device)
    ...
```

Here are some guidelines for building your binary classification CNN from scratch:

- You may use any architecture you like.
- This is the path to the data in your notebook: `../input/cat-breed/cat-breed/`
- You should use an `IMAGE_SIZE = 200` pixels in your data loader (the raw images could be any size).
- **You must train your model for at least 20 epochs and print or plot the accuracy for each epoch on the validation data for us to see.**

> If you want to take a look at the images after making a `train_loader`, try this code:

```
# Plot samples
sample_batch = next(iter(train_loader))
plt.figure(figsize=(10, 8)); plt.axis("off"); plt.title("Sample Training
Images")
plt.imshow(np.transpose(utils.make_grid(sample_batch[0], padding=1,
normalize=True),(1, 2, 0)));
```

In [15]:

```
#data load train
TRAIN_DIR = '../input/cat-breed/cat-breed/TRAIN'
train_dataset = datasets.ImageFolder(root=TRAIN_DIR)
#data load test
TEST_DIR = '../input/cat-breed/cat-breed/TEST'
test_dataset = datasets.ImageFolder(root=TEST_DIR)
```

In [17]:

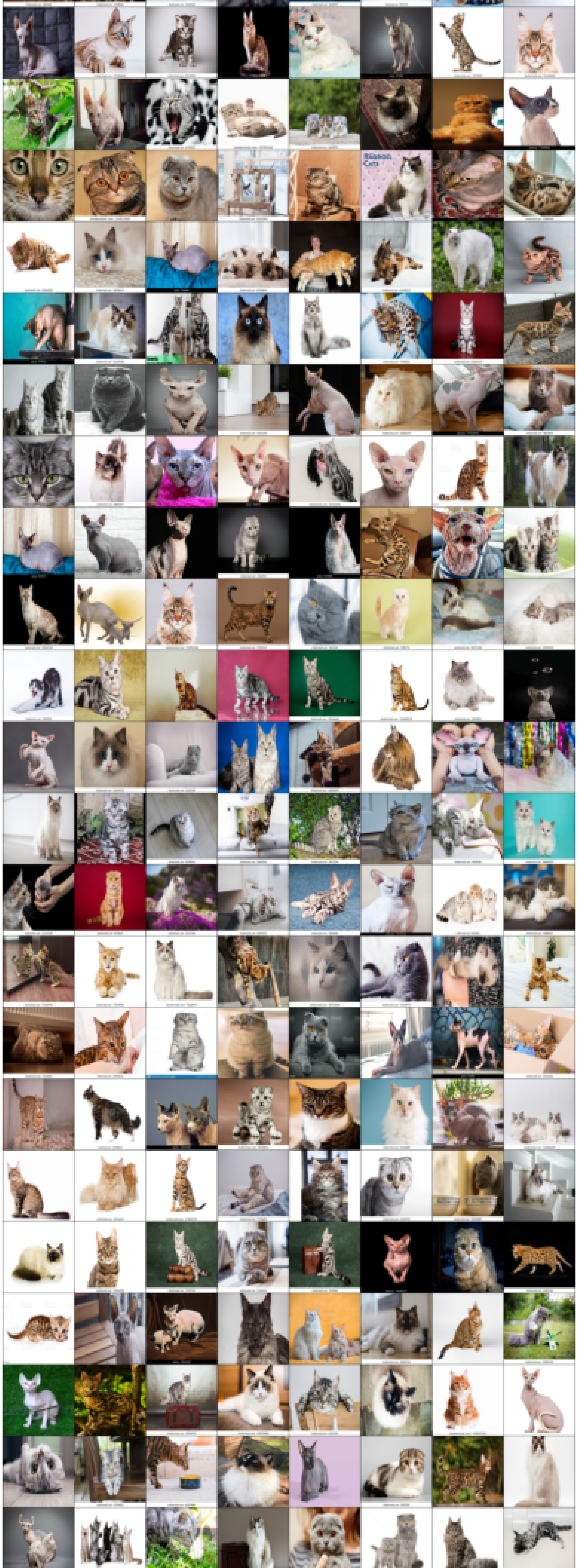
```
IMAGE_SIZE = (200, 200)

data_transforms = transforms.Compose([
    transforms.Resize(IMAGE_SIZE),
    transforms.ToTensor()
])
# load data with size 200
train_dataset = datasets.ImageFolder(root=TRAIN_DIR, transform=data_transforms)
test_dataset = datasets.ImageFolder(root=TEST_DIR, transform=data_transforms)
```

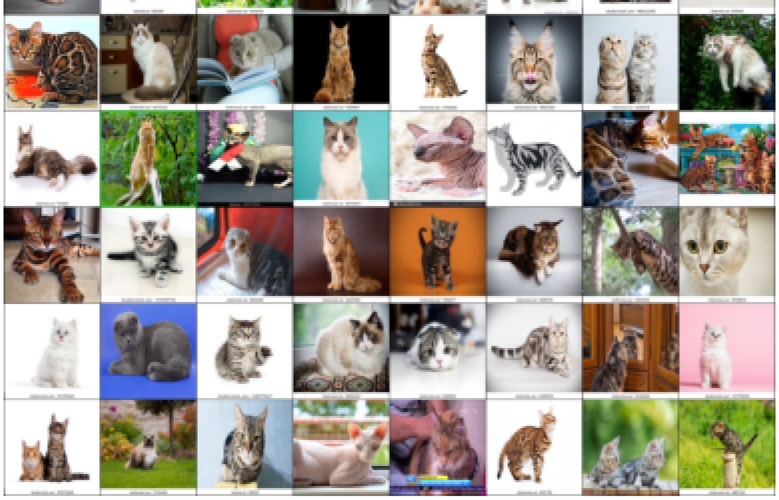
In [19]:

```
BATCH_SIZE = 256
#data loader
trainloader = torch.utils.data.DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=
validloader = torch.utils.data.DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=T
```

In [21]:

```
# Plot samples
sample_batch = next(iter(trainloader))
plt.figure(figsize=(20, 20)); plt.axis("off"); plt.title("Sample Training Images")
plt.imshow(np.transpose(utils.make_grid(sample_batch[0], padding=1, normalize=True),(1,
```





In [18]:
```
#Create CNN
class CNN(nn.Module):
    def __init__(self):
        super().__init__()
        self.main = nn.Sequential(
            nn.Conv2d(3, 32, (5, 5)),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d((2, 2)),
            nn.Dropout(0.2),

            nn.Conv2d(32, 16, (5, 5)),
            nn.BatchNorm2d(16),
            nn.ReLU(),
            nn.MaxPool2d((2, 2)),

            nn.Conv2d(16, 8, (3, 3)),
            nn.BatchNorm2d(8),
            nn.ReLU(),

            nn.Conv2d(8, 4, (3, 3)),
            nn.BatchNorm2d(4),
            nn.ReLU(),


            nn.Flatten(),
            nn.Linear(7396, 1024),
            nn.ReLU(),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Linear(512, 128),
            nn.ReLU(),
            nn.Linear(128, 6)
        )

    def forward(self, x):
        out = self.main(x)
        return out
```

In [20]:
```
def trainer(model, criterion, optimizer, train_loader, valid_loader, device, epochs=20,
    """Simple training wrapper for PyTorch network."""

    train_accuracy = []
    valid_accuracy = []
    for epoch in range(epochs):  # for each epoch
        train_batch_loss = 0
        train_batch_acc = 0
        valid_batch_loss = 0
```

```
        valid_batch_acc = 0

        # Training
        for X, y in train_loader:
            if device.type in ['cuda', 'mps']:
                X, y = X.to(device), y.to(device)
            optimizer.zero_grad()
            y_hat = model(X)
            y_hat_labels = torch.argmax(y_hat.detach(), dim = 1)
            loss = criterion(y_hat, y)
            loss.backward()
            optimizer.step()
            train_batch_loss += loss.item()
            train_batch_acc += (y_hat_labels == y).type(torch.float32).mean().item()
        train_accuracy.append(train_batch_acc / len(train_loader))

        # Validation
        model.eval()
        with torch.no_grad():
            for X, y in valid_loader:
                if device.type in ['cuda', 'mps']:
                    X, y = X.to(device), y.to(device)
                y_hat = model(X)
                y_hat_labels = torch.argmax(y_hat.detach(), dim = 1)
                loss = criterion(y_hat, y)
                valid_batch_loss += loss.item()
                valid_batch_acc += (y_hat_labels == y).type(torch.float32).mean().item()
        valid_accuracy.append(valid_batch_acc / len(valid_loader))
        model.train()

        # Print progress
        if verbose:
            print(f"Epoch {epoch + 1}:",
                  f"Train Accuracy: {train_accuracy[-1]:.2f}",
                  f"Valid Accuracy: {valid_accuracy[-1]:.2f}")

    return {"train_accuracy": train_accuracy, "valid_accuracy": valid_accuracy}
```

In [ ]:

```
model = CNN()
model.to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optimizer = optim.Adam(model.parameters(), lr=2e-4)
results = trainer(model, criterion, optimizer, trainloader, validloader, device, epochs=
```

1. Epoch 1: Train Accuracy: 0.27 Valid Accuracy: 0.16
2. Epoch 2: Train Accuracy: 0.44 Valid Accuracy: 0.20
3. Epoch 3: Train Accuracy: 0.54 Valid Accuracy: 0.19
4. Epoch 4: Train Accuracy: 0.56 Valid Accuracy: 0.17
5. Epoch 5: Train Accuracy: 0.61 Valid Accuracy: 0.16
6. Epoch 6: Train Accuracy: 0.65 Valid Accuracy: 0.21
7. Epoch 7: Train Accuracy: 0.69 Valid Accuracy: 0.20
8. Epoch 8: Train Accuracy: 0.71 Valid Accuracy: 0.27
9. Epoch 9: Train Accuracy: 0.76 Valid Accuracy: 0.18
10. Epoch 10: Train Accuracy: 0.80 Valid Accuracy: 0.29
11. Epoch 11: Train Accuracy: 0.83 Valid Accuracy: 0.33
12. Epoch 12: Train Accuracy: 0.87 Valid Accuracy: 0.42
13. Epoch 13: Train Accuracy: 0.91 Valid Accuracy: 0.48
14. Epoch 14: Train Accuracy: 0.93 Valid Accuracy: 0.51
15. Epoch 15: Train Accuracy: 0.95 Valid Accuracy: 0.52

16. Epoch 16: Train Accuracy: 0.96 Valid Accuracy: 0.56
17. Epoch 17: Train Accuracy: 0.97 Valid Accuracy: 0.55
18. Epoch 18: Train Accuracy: 0.99 Valid Accuracy: 0.59
19. Epoch 19: Train Accuracy: 0.99 Valid Accuracy: 0.57
20. Epoch 20: Train Accuracy: 0.99 Valid Accuracy: 0.54

1.2: Feature Extractor

In this exercise, you should leverage a pre-trained model customized with your own layer(s) on top, to build a CNN classifier that can identify various cat breeds.

- You can use any model you wish. I used `DenseNet`.
- Train your model for at least 20 epochs.
- Comment on the performance of this model compared to your "from scratch" model.

the performance is much better than my scratch model

In [ ]:
```
densenet = models.densenet121(pretrained=True)
for param in densenet.parameters():   # Freeze parameters so we don't update them
    param.requires_grad = False
```

In [ ]:
```
densenet.to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(densenet.parameters(), lr=2e-3)
results = trainer(densenet, criterion, optimizer, trainloader, validloader, device, epoc
```

1. Epoch 1: Train Accuracy: 0.57 Valid Accuracy: 0.46
2. Epoch 2: Train Accuracy: 0.80 Valid Accuracy: 0.81
3. Epoch 3: Train Accuracy: 0.90 Valid Accuracy: 0.89
4. Epoch 4: Train Accuracy: 0.93 Valid Accuracy: 0.94
5. Epoch 5: Train Accuracy: 0.95 Valid Accuracy: 0.87
6. Epoch 6: Train Accuracy: 0.96 Valid Accuracy: 0.90
7. Epoch 7: Train Accuracy: 0.96 Valid Accuracy: 0.86
8. Epoch 8: Train Accuracy: 0.97 Valid Accuracy: 0.91
9. Epoch 9: Train Accuracy: 0.97 Valid Accuracy: 0.92
10. Epoch 10: Train Accuracy: 0.98 Valid Accuracy: 0.90
11. Epoch 11: Train Accuracy: 0.99 Valid Accuracy: 0.95
12. Epoch 12: Train Accuracy: 0.99 Valid Accuracy: 0.91
13. Epoch 13: Train Accuracy: 0.99 Valid Accuracy: 0.91
14. Epoch 14: Train Accuracy: 0.99 Valid Accuracy: 0.89
15. Epoch 15: Train Accuracy: 1.00 Valid Accuracy: 0.90
16. Epoch 16: Train Accuracy: 1.00 Valid Accuracy: 0.92
17. Epoch 17: Train Accuracy: 0.99 Valid Accuracy: 0.93
18. Epoch 18: Train Accuracy: 0.99 Valid Accuracy: 0.90
19. Epoch 19: Train Accuracy: 1.00 Valid Accuracy: 0.92
20. Epoch 20: Train Accuracy: 1.00 Valid Accuracy: 0.93

1.3: Fine Tuning

In this final exercise, you should fine-tune your model by updating all or some of the layers during training.

- You can fine-tune as many layers as you like: the whole model, or particular layers. Experiment with both modes of fine-tuning, and find which works better.
- Train your model for at least 20 epochs.
- Comment on the performance of this model compared to your "from scratch" and "feature extractor" models.

The overall performance is much better than scratch and slightly better tahn feature extractor.

In [ ]:
```
new_layers = nn.Sequential(
    nn.Linear(1024, 512),
    nn.ReLU(),
    nn.Linear(512, 128),
    nn.ReLU(),
    nn.Linear(128, 6)
)
densenet.classifier = new_layers
# Freeze all but the last three layers
for layer in densenet.features[:-3]:
    for param in layer.parameters():
        param.requires_grad = False
```

In [ ]:
```
densenet.to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(densenet.parameters(), lr=2e-3)
results = trainer(densenet, criterion, optimizer, trainloader, validloader, device, epoc
```

1. Epoch 1: Train Accuracy: 0.86 Valid Accuracy: 0.70
2. Epoch 2: Train Accuracy: 0.92 Valid Accuracy: 0.91
3. Epoch 3: Train Accuracy: 0.93 Valid Accuracy: 0.86
4. Epoch 4: Train Accuracy: 0.99 Valid Accuracy: 0.90
5. Epoch 5: Train Accuracy: 0.99 Valid Accuracy: 0.88
6. Epoch 6: Train Accuracy: 1.00 Valid Accuracy: 0.94
7. Epoch 7: Train Accuracy: 1.00 Valid Accuracy: 0.95
8. Epoch 8: Train Accuracy: 1.00 Valid Accuracy: 0.93
9. Epoch 9: Train Accuracy: 1.00 Valid Accuracy: 0.94
10. Epoch 10: Train Accuracy: 1.00 Valid Accuracy: 0.90
11. Epoch 11: Train Accuracy: 1.00 Valid Accuracy: 0.93
12. Epoch 12: Train Accuracy: 1.00 Valid Accuracy: 0.94
13. Epoch 13: Train Accuracy: 1.00 Valid Accuracy: 0.95
14. Epoch 14: Train Accuracy: 1.00 Valid Accuracy: 0.91
15. Epoch 15: Train Accuracy: 1.00 Valid Accuracy: 0.93
16. Epoch 16: Train Accuracy: 1.00 Valid Accuracy: 0.92
17. Epoch 17: Train Accuracy: 1.00 Valid Accuracy: 0.92
18. Epoch 18: Train Accuracy: 1.00 Valid Accuracy: 0.93
19. Epoch 19: Train Accuracy: 1.00 Valid Accuracy: 0.95
20. Epoch 20: Train Accuracy: 1.00 Valid Accuracy: 0.94

Exercise 2: Generative Adversarial Networks

rubric={accuracy:15}

In this exercise you're going to practice building a generative adversarial network (GAN).

GANs are incredibly hard to train especially with small datasets, so you may not get good results in this exercise. But don't worry about that, it is just important to get some practice and experience with these types of NNs.

> For this exercise, you're not limited to a particular dataset, you can use any dataset you like. The `cat-breed` or any other suitable one on Kaggle is acceptable, as long as you can show the progress of your trained GAN on it.

2.1: Preparing the Data

In Kaggle, running the follow cell should print out `"Using device: cuda"` which means a GPU is available:

In [ ]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device.type}")
```

To make use of the GPU, you should:

- Move your model to the GPU after creating it with the syntax:

```
model.to(device)
```

- In your training loop, each batch should be moved to the GPU using syntax like:

```
for X, _ in dataloader:
    X = X.to(device)
    ...
```

- Note above that we don't need the labels for training a GAN, so I ignore it by un-packing it into an underscore `_` (which is typically Python convention for variables we don't need).

Okay, prepare the data by creating a `data_loader`. This is the path to the data in your notebook if you choose to use the `cat-breed` dataset: `../input/cat-breed/cat-breed/`.

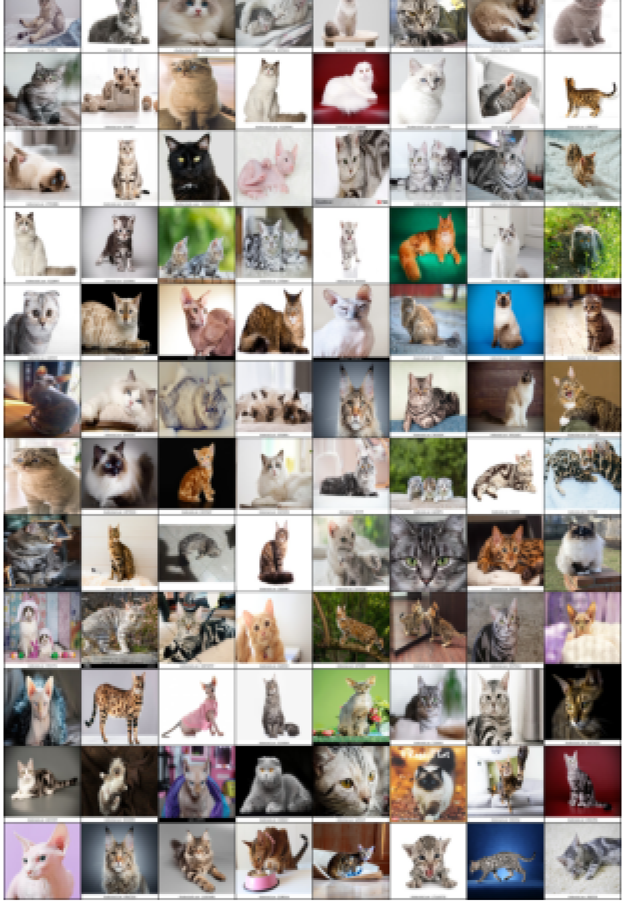
> If you want to take a look at the images after making a `data_loader`, try this code:

```
# Plot samples
sample_batch = next(iter(data_loader))
plt.figure(figsize=(10, 8)); plt.axis("off"); plt.title("Sample Training Images")
plt.imshow(np.transpose(utils.make_grid(sample_batch[0], padding=1, normalize=True),(1, 2, 0)));
```

In [64]:
```
#data load
DATA_DIR = 'cat-breed/'
dataset = datasets.ImageFolder(root=DATA_DIR)
IMAGE_SIZE = (128, 128)
```

```
data_transforms = transforms.Compose([
    transforms.Resize(IMAGE_SIZE),
    transforms.ToTensor()
])
# load data with size 128
dataset = datasets.ImageFolder(root=DATA_DIR, transform=data_transforms)
BATCH_SIZE = 256
#data loader
data_loader = torch.utils.data.DataLoader(dataset, batch_size=BATCH_SIZE, shuffle=True)
```

In [65]:
```
# Plot samples
sample_batch = next(iter(data_loader))
plt.figure(figsize=(20, 16)); plt.axis("off"); plt.title("Sample Training Images")
plt.imshow(np.transpose(utils.make_grid(sample_batch[0], padding=1, normalize=True),(1,
```



2.2: Create the Generator

Now, we need to create a generator for our GAN. You can reuse/modify the code from Lecture 8, or build your own.

In [23]:
```
class Generator(nn.Module):

    def __init__(self, LATENT_SIZE):
        super(Generator, self).__init__()

        self.main = nn.Sequential(

            # input dim: [-1, LATENT_SIZE, 1, 1]

            nn.ConvTranspose2d(LATENT_SIZE, 1024, kernel_size=4, stride=1, padding=0, bi
            nn.BatchNorm2d(1024),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 1024, 4, 4]

            nn.ConvTranspose2d(1024, 512, kernel_size=4, stride=2, padding=1, bias=False
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 512, 8, 8]

            nn.ConvTranspose2d(512, 256, kernel_size=4, stride=2, padding=1, bias=False)
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 256, 16, 16]

            nn.ConvTranspose2d(256, 128, kernel_size=4, stride=2, padding=1, bias=False)
            nn.BatchNorm2d(128),
```

```
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 128, 32, 32]

            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(64),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 64, 64, 64]

            nn.ConvTranspose2d(64, 3, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(3),

            # output dim: [-1, 3, 128, 128]

            nn.Tanh()

            # output dim: [-1, 3, 128, 128]
        )

    def forward(self, input):
        output = self.main(input)
        return output
```

2.3: Create the Discriminator

Now, we need to create a discriminator for our GAN. You can reuse/modify the code from Lecture 8, or build your own.

In [63]:

```
class Discriminator(nn.Module):

    def __init__(self):
        super(Discriminator, self).__init__()

        self.main = nn.Sequential(

            # input dim: [-1, 3, 128, 128]

            nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(64),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 64, 64, 64]

            nn.Conv2d(64, 64, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(64),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 64, 32, 32]

            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 128, 16, 16]

            nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 256, 8, 8]

            nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1, bias=False),
```

```
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),

            # output dim: [-1, 512, 4, 4]

            nn.Conv2d(512, 1, kernel_size=4, stride=1, padding=0),

            # output dim: [-1, 1, 1, 1]

            nn.Flatten(),

            # output dim: [-1]

            nn.Sigmoid()

            # output dim: [-1]
        )

    def forward(self, input):
        output = self.main(input)
        return output
```

2.4: Initialize Weights

GANs can be quite sensitive to the initial weights assigned to each layer when we instantiate the model. Instantiate your generator and discriminator and then specify their initial weights as follows:

- `Conv2d()` layers: normal distribution with `mean=0.0` and `std=0.02`
- `ConvTranspose2d()` layers: normal distribution with `mean=0.0` and `std=0.02`
- `BatchNorm2d()` layers: normal distribution with `mean=1.0` and `std=0.02` for the weights, zeroes for the biases
- Use `LATENT_SIZE = 100`

In [28]:

```
LATENT_SIZE = 100

generator = Generator(LATENT_SIZE)
discriminator = Discriminator()

generator.to(device)
discriminator.to(device)

criterion = nn.BCELoss()

optimizerG = optim.Adam(generator.parameters(), lr=0.001, betas=(0.5, 0.999))
optimizerD = optim.Adam(discriminator.parameters(), lr=0.001, betas=(0.5, 0.999))
```

In [29]:

```
def weights_init(m):
    if isinstance(m, (nn.Conv2d, nn.ConvTranspose2d)):
        nn.init.normal_(m.weight.data, 0.0, 0.02)
    elif isinstance(m, nn.BatchNorm2d):
        nn.init.normal_(m.weight.data, 1.0, 0.02)
        nn.init.constant_(m.bias.data, 0)

generator.apply(weights_init)
discriminator.apply(weights_init);
```

2.5: Train your GAN

You now have all the ingredients you need now to train a GAN, so give it a go!

You should track the loss of your model as epochs progress and show at least one example of an image output by your trained generator (better yet, record the evolution over time of how your generator is doing, like we did in Lecture 8). **Your results may not be great and that's perfectly okay, you should just show *something***.

Here are some tips:

- You will likely need to train for at least `NUM_EPOCHS=100` (and maybe more).
- I find that the hardest part about training GANs is that the discriminator "overpowers" the generator, making it hard for the generator to learn how to create realistic images. There are lots of things you can do to try and balance your generator and discriminator, such as: play with the optimizer's hyperparameters, change the architectures of your models, etc.
- Here's a good set of tips and tricks for training GANs.
- Once again, GANs are notoriously difficult to train (even more so with smaller data sets like we have here). Don't worry if you're not getting amazing results. This is all about practice.

In [30]:
```
img_list = []
fixed_noise = torch.randn(BATCH_SIZE, LATENT_SIZE, 1, 1).to(device)
```

In [ ]:
```
NUM_EPOCHS = 100

print('Training started:\n')

D_real_epoch, D_fake_epoch, loss_dis_epoch, loss_gen_epoch = [], [], [], []

for epoch in range(NUM_EPOCHS):

    D_real_iter, D_fake_iter, loss_dis_iter, loss_gen_iter = [], [], [], []

    for real_batch, _ in data_loader:

        # STEP 1: train discriminator
        # ==================================
        # Train with real data
        discriminator.zero_grad()

        real_batch = real_batch.to(device)
        real_labels = torch.ones((real_batch.shape[0],), dtype=torch.float).to(device)

        output = discriminator(real_batch).view(-1)
        loss_real = criterion(output, real_labels)

        # Iteration book-keeping
        D_real_iter.append(output.mean().item())

        # Train with fake data
        noise = torch.randn(real_batch.shape[0], LATENT_SIZE, 1, 1).to(device)

        fake_batch = generator(noise)
        fake_labels = torch.zeros_like(real_labels)

        output = discriminator(fake_batch.detach()).view(-1)
        loss_fake = criterion(output, fake_labels)
```

```python
        # Update discriminator weights
        loss_dis = loss_real + loss_fake
        loss_dis.backward()
        optimizerD.step()

        # Iteration book-keeping
        loss_dis_iter.append(loss_dis.mean().item())
        D_fake_iter.append(output.mean().item())

        # STEP 2: train generator
        # ==================================
        generator.zero_grad()
        output = discriminator(fake_batch).view(-1)
        loss_gen = criterion(output, real_labels)
        loss_gen.backward()

        # Book-keeping
        loss_gen_iter.append(loss_gen.mean().item())

        # Update generator weights and store loss
        optimizerG.step()

    print(f"Epoch ({epoch + 1}/{NUM_EPOCHS})\t",
          f"Loss_G: {mean(loss_gen_iter):.4f}",
          f"Loss_D: {mean(loss_dis_iter):.4f}\t",
          f"D_real: {mean(D_real_iter):.4f}",
          f"D_fake: {mean(D_fake_iter):.4f}")

    # Epoch book-keeping
    loss_gen_epoch.append(mean(loss_gen_iter))
    loss_dis_epoch.append(mean(loss_dis_iter))
    D_real_epoch.append(mean(D_real_iter))
    D_fake_epoch.append(mean(D_fake_iter))

    # Keeping track of the evolution of a fixed noise latent vector
    with torch.no_grad():
        fake_images = generator(fixed_noise).detach().cpu()
        img_list.append(utils.make_grid(fake_images, normalize=True, nrows=10))

print("\nTraining ended.")
```

In [67]:
```python
from IPython.display import Image
Image('q2_1.png')
```

Out[67]:

```
Training started:

Epoch (1/50)     Loss_G: 25.7434 Loss_D: 20.4364        D_real: 0.7266 D_fake: 0.5718
Epoch (2/50)     Loss_G: 16.9031 Loss_D: 1.6255  D_real: 0.8401 D_fake: 0.3072
Epoch (3/50)     Loss_G: 10.5970 Loss_D: 1.2394  D_real: 0.8405 D_fake: 0.2940
Epoch (4/50)     Loss_G: 9.7646 Loss_D: 0.8072   D_real: 0.8908 D_fake: 0.1471
Epoch (5/50)     Loss_G: 6.4856 Loss_D: 1.3153   D_real: 0.8161 D_fake: 0.2233
Epoch (6/50)     Loss_G: 9.5083 Loss_D: 0.2293   D_real: 0.9710 D_fake: 0.1332
Epoch (7/50)     Loss_G: 6.7445 Loss_D: 0.1235   D_real: 0.9852 D_fake: 0.0792
Epoch (8/50)     Loss_G: 6.5112 Loss_D: 0.0469   D_real: 0.9898 D_fake: 0.0316
Epoch (9/50)     Loss_G: 5.3430 Loss_D: 0.0907   D_real: 0.9930 D_fake: 0.0728
Epoch (10/50)    Loss_G: 5.1870 Loss_D: 0.0479   D_real: 0.9893 D_fake: 0.0343
Epoch (11/50)    Loss_G: 22.3778 Loss_D: 5.3078  D_real: 0.5988 D_fake: 0.1993
Epoch (12/50)    Loss_G: 5.3780 Loss_D: 0.2016   D_real: 0.9805 D_fake: 0.0985
Epoch (13/50)    Loss_G: 7.8901 Loss_D: 0.3509   D_real: 0.9336 D_fake: 0.1032
Epoch (14/50)    Loss_G: 6.5371 Loss_D: 0.2225   D_real: 0.9624 D_fake: 0.1186
Epoch (15/50)    Loss_G: 5.7455 Loss_D: 0.1380   D_real: 0.9756 D_fake: 0.0881
Epoch (16/50)    Loss_G: 6.3077 Loss_D: 0.4381   D_real: 0.9165 D_fake: 0.1463
Epoch (17/50)    Loss_G: 6.4466 Loss_D: 0.4110   D_real: 0.9556 D_fake: 0.2373
Epoch (18/50)    Loss_G: 9.7270 Loss_D: 0.0255   D_real: 0.9814 D_fake: 0.0004
Epoch (19/50)    Loss_G: 6.9803 Loss_D: 0.0087   D_real: 0.9983 D_fake: 0.0068
Epoch (20/50)    Loss_G: 5.2147 Loss_D: 0.0468   D_real: 0.9982 D_fake: 0.0433
Epoch (21/50)    Loss_G: 5.4467 Loss_D: 0.0301   D_real: 0.9964 D_fake: 0.0254
Epoch (22/50)    Loss_G: 6.8885 Loss_D: 0.1329   D_real: 0.9693 D_fake: 0.0791
Epoch (23/50)    Loss_G: 5.7776 Loss_D: 0.2102   D_real: 0.9174 D_fake: 0.0315
Epoch (24/50)    Loss_G: 5.9971 Loss_D: 1.0324   D_real: 0.9885 D_fake: 0.2175
Epoch (25/50)    Loss_G: 5.1186 Loss_D: 2.2944   D_real: 0.6697 D_fake: 0.0378
Epoch (26/50)    Loss_G: 4.3400 Loss_D: 0.1629   D_real: 0.9914 D_fake: 0.1165
Epoch (27/50)    Loss_G: 5.3773 Loss_D: 0.0802   D_real: 0.9838 D_fake: 0.0370
Epoch (28/50)    Loss_G: 5.3289 Loss_D: 0.0809   D_real: 0.9937 D_fake: 0.0638
Epoch (29/50)    Loss_G: 5.7751 Loss_D: 0.1174   D_real: 0.9931 D_fake: 0.0955
Epoch (30/50)    Loss_G: 7.4546 Loss_D: 0.5805   D_real: 0.9674 D_fake: 0.2066
Epoch (31/50)    Loss_G: 5.7769 Loss_D: 0.6867   D_real: 0.7897 D_fake: 0.0227
Epoch (32/50)    Loss_G: 4.0814 Loss_D: 0.1462   D_real: 0.9905 D_fake: 0.1232
Epoch (33/50)    Loss_G: 4.7710 Loss_D: 0.1465   D_real: 0.9655 D_fake: 0.0921
Epoch (34/50)    Loss_G: 7.2592 Loss_D: 0.2830   D_real: 0.9323 D_fake: 0.0707
Epoch (35/50)    Loss_G: 5.3059 Loss_D: 0.0763   D_real: 0.9852 D_fake: 0.0560
Epoch (36/50)    Loss_G: 7.3652 Loss_D: 0.0338   D_real: 0.9802 D_fake: 0.0105
Epoch (37/50)    Loss_G: 5.6034 Loss_D: 1.6159   D_real: 0.7931 D_fake: 0.2452
Epoch (38/50)    Loss_G: 4.6647 Loss_D: 0.5182   D_real: 0.9351 D_fake: 0.0746
Epoch (39/50)    Loss_G: 4.6155 Loss_D: 0.7134   D_real: 0.9748 D_fake: 0.1460
Epoch (40/50)    Loss_G: 6.3373 Loss_D: 0.1310   D_real: 0.9528 D_fake: 0.0316
Epoch (41/50)    Loss_G: 6.7136 Loss_D: 0.2731   D_real: 0.9951 D_fake: 0.0402
Epoch (42/50)    Loss_G: 5.3184 Loss_D: 0.0765   D_real: 0.9921 D_fake: 0.0617
Epoch (43/50)    Loss_G: 4.2110 Loss_D: 0.0891   D_real: 0.9953 D_fake: 0.0780
Epoch (44/50)    Loss_G: 7.0556 Loss_D: 2.4893   D_real: 0.8277 D_fake: 0.1405
Epoch (45/50)    Loss_G: 3.6863 Loss_D: 1.2938   D_real: 0.7666 D_fake: 0.1503
Epoch (46/50)    Loss_G: 3.9906 Loss_D: 0.1449   D_real: 0.9751 D_fake: 0.1003
Epoch (47/50)    Loss_G: 3.7744 Loss_D: 0.1375   D_real: 0.9650 D_fake: 0.0780
Epoch (48/50)    Loss_G: 3.6686 Loss_D: 0.1218   D_real: 0.9728 D_fake: 0.0778
Epoch (49/50)    Loss_G: 3.8003 Loss_D: 0.0956   D_real: 0.9720 D_fake: 0.0572
Epoch (50/50)    Loss_G: 3.6261 Loss_D: 0.0904   D_real: 0.9793 D_fake: 0.0630

Training ended.
```

In [ ]:

```
%%capture

fig = plt.figure(figsize=(10, 10))
ims = [[plt.imshow(np.transpose(i,(1, 2, 0)), animated=True)] for i in img_list[::1]]
ani = animation.ArtistAnimation(fig, ims, interval=1000, repeat_delay=1000, blit=True)
ani.save('GAN.gif', writer='imagemagick', fps=2)
```

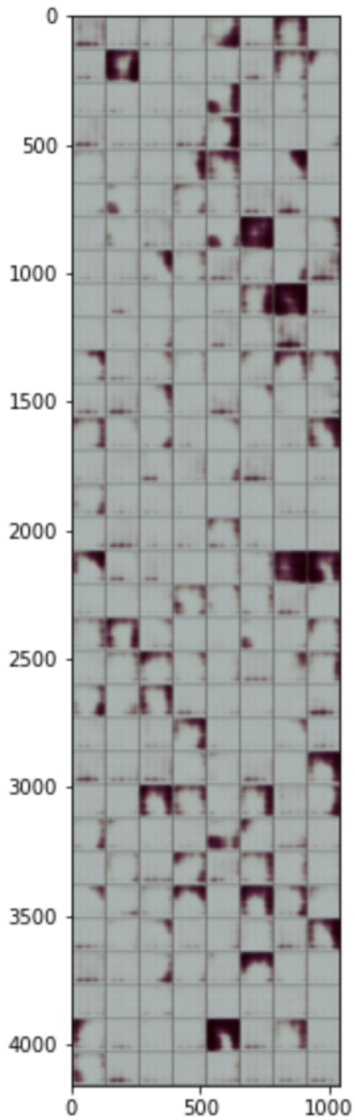
In [ ]:

```
HTML(ani.to_jshtml())
```

In [68]:

```
Image('q2_2.png')
```

Out[68]:



In [ ]: