# EECS 442 PS8: Representation learning

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# Starting

Run the following code to import the modules you'll need. After your finish the assignment, remember to run all cells and save the note book to your local machine as a .ipynb file for Canvas submission.

In [1]:

```
!pip install torchsummary
import pickle
import numpy as np
import matplotlib.pyplot as plt
import os
import time
import itertools

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset

import torchvision
from torchvision import datasets, models, transforms

from torchsummary import summary
from tqdm import tqdm_notebook

print("PyTorch Version: ",torch.__version__)
print("Torchvision Version: ",torchvision.__version__)
# Detect if we have a GPU available
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
if torch.cuda.is_available():
    print("Using the GPU!")
else:
    print("WARNING: Could not find GPU! Using CPU only. If you want to enable G

np.random.seed(42)
torch.manual_seed(42)
torch.cuda.manual_seed_all(42)
```

```
Requirement already satisfied: torchsummary in /usr/local/lib/python3.7/dist-pa
ckages (1.5.1)
PyTorch Version:  1.10.0+cu111
Torchvision Version:  0.11.1+cu111
WARNING: Could not find GPU! Using CPU only. If you want to enable GPU, please
to go Edit > Notebook Settings > Hardware Accelerator and select GPU.
```

# Pset 8. Self-supervised learning

In this problem, we are going to implement two representation learning methods: an autoencoder and a recent constrastive learning method. We'll then test the features that were learned by these models on a "downstream" recognition task, using the STL-10 dataset.

# Downloading the dataset.

We use PyTorch built-in class to download the STL-10 (http://ai.stanford.edu/~acoates/stl10/) dataset (a subset of ImageNet). The STL-10 dataset contains three partitions: train, test, and unlabeled. The train partition contains 10 image classes, each class with 500 images. The test partition contains 800 images for each class. The unlabeled contains a total of 100,000 images with many classes not in the train/test partitions.

In [2]:

```
unlabeled_transform = transforms.Compose([transforms.RandomHorizontalFlip(),
                                          transforms.RandomCrop(64),
                                          transforms.ToTensor()])

labeled_transform = transforms.Compose([transforms.CenterCrop(64),
                                        transforms.ToTensor()])


# We use the PyTorch built-in class to download the STL-10 dataset.
# The 'unlabeled' partition contains 100,000 images without labels.
# It's used for leanring representations with unsupervised learning.
dataset_un = torchvision.datasets.STL10('./data', 'unlabeled', download=True, t

dataset_tr = torchvision.datasets.STL10('./data', 'train', download=False, tran
dataset_te = torchvision.datasets.STL10('./data', 'test', download=False, trans
```

```
Downloading http://ai.stanford.edu/~acoates/stl10/stl10_binary.tar.gz to ./dat
a/stl10_binary.tar.gz

Extracting ./data/stl10_binary.tar.gz to ./data
```

In [3]:

```
print('# of samples for ulabeled, train, and test, {}, {}, {}'.format(len(datas
print('Classes in train: {}'.format(dataset_tr.classes))
```

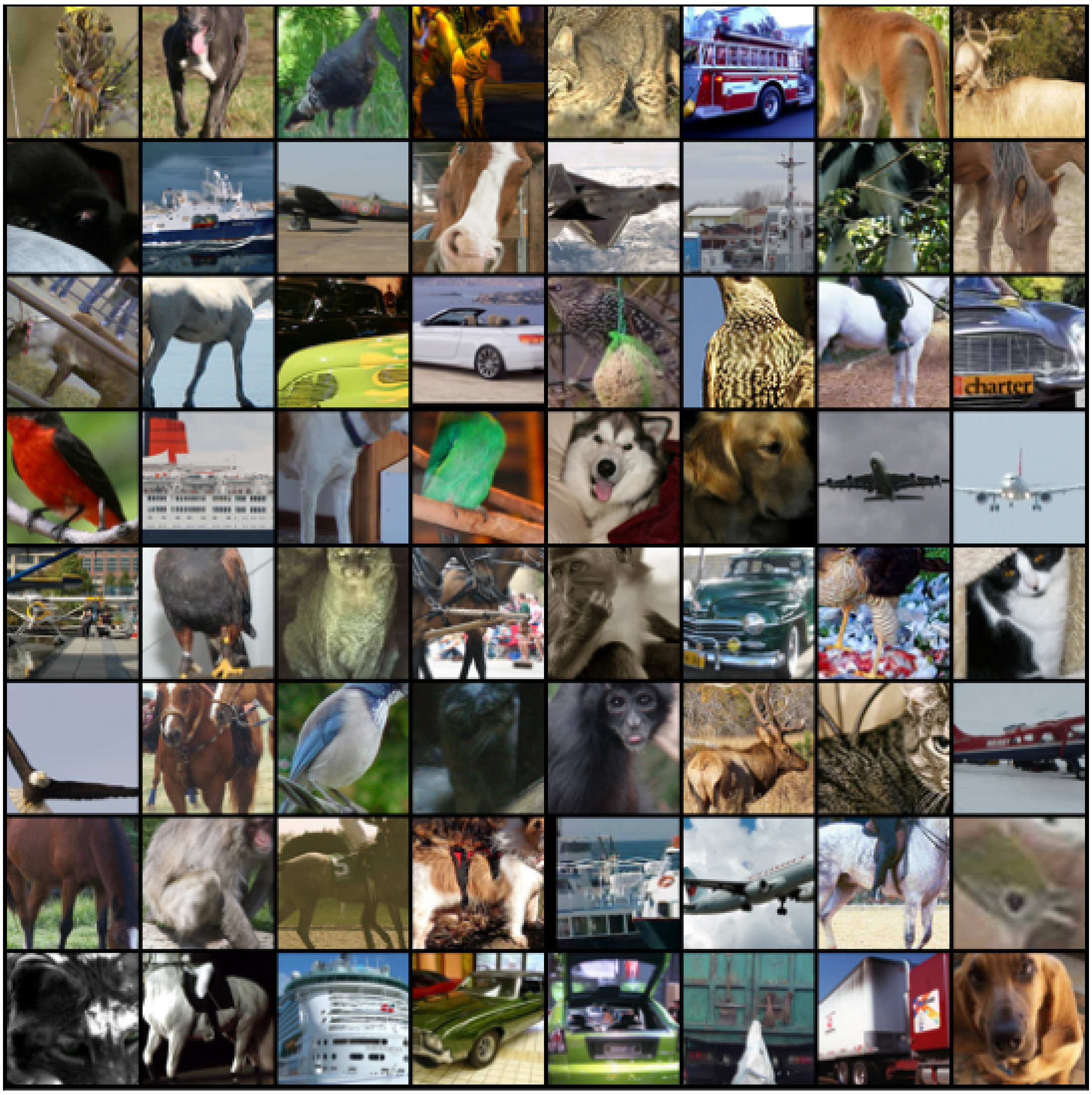
```
# of samples for ulabeled, train, and test, 100000, 5000, 8000
Classes in train: ['airplane', 'bird', 'car', 'cat', 'deer', 'dog', 'horse', 'm
onkey', 'ship', 'truck']
```

In [4]:

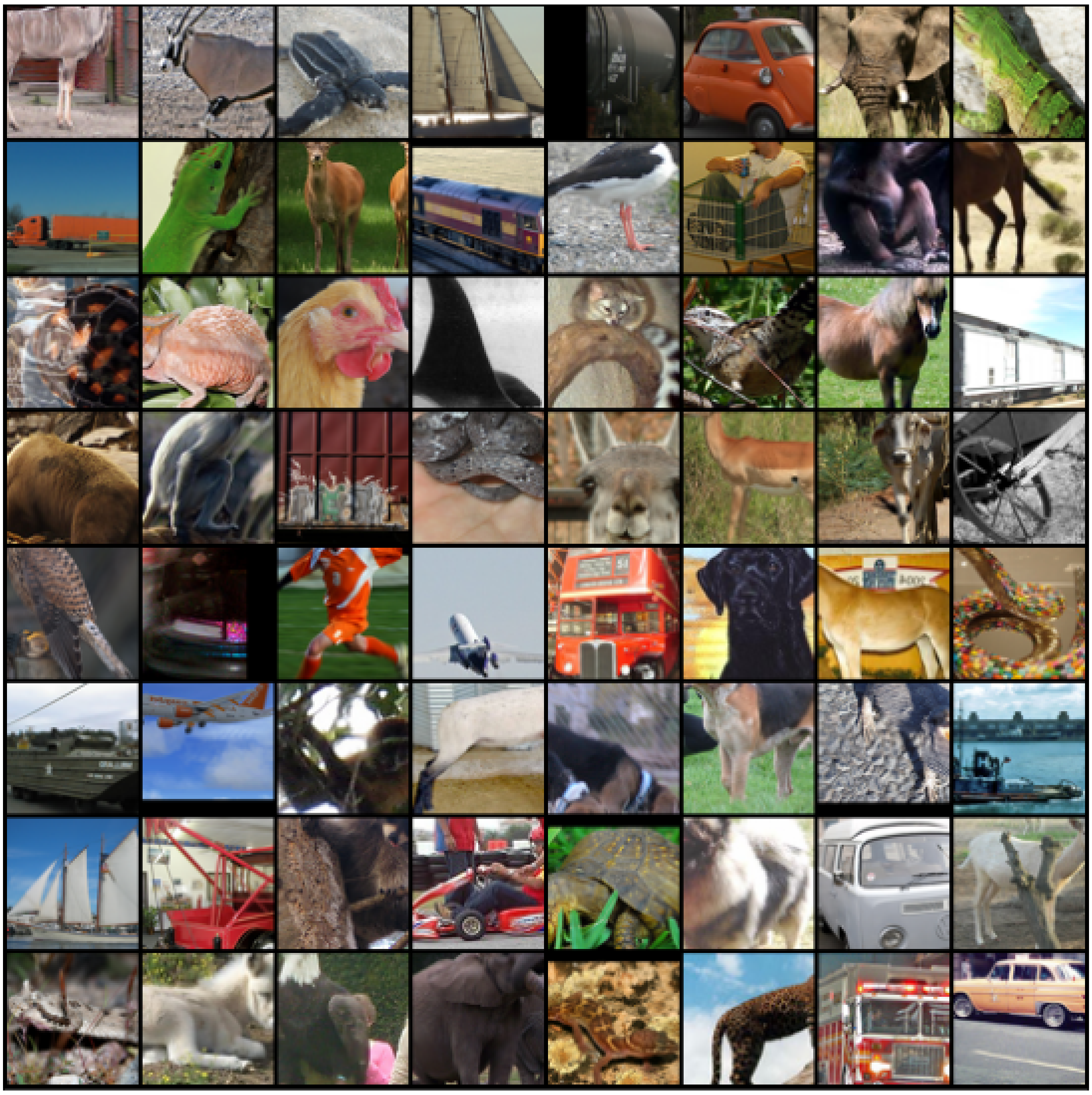
```
# Visualize the data within the dataset
class_names = dict(zip(range(10), dataset_tr.classes))
dataloader_un = DataLoader(dataset_un, batch_size=64)
dataloader_tr = DataLoader(dataset_tr, batch_size=64)

def imshow(inp, title=None, ax=None, figsize=(5, 5)):
  """Imshow for Tensor."""
  inp = inp.numpy().transpose((1, 2, 0))
  if ax is None:
    fig, ax = plt.subplots(1, figsize=figsize)
  ax.imshow(inp)
  ax.set_xticks([])
  ax.set_yticks([])
  if title is not None:
    ax.set_title(title)

# Visualize training partition
# Get a batch of training data
inputs, classes = next(iter(dataloader_tr))
```

```python
# Make a grid from batch
out = torchvision.utils.make_grid(inputs, nrow=8)

fig, ax = plt.subplots(1, figsize=(10, 10))
title = [class_names[x.item()] if (i+1) % 8 != 0 else class_names[x.item()]+'\n
imshow(out, title=' | '.join(title), ax=ax)

# Visualize unlabeled partition
inputs, classes = next(iter(dataloader_un))
out = torchvision.utils.make_grid(inputs, nrow=8)

fig, ax = plt.subplots(1, figsize=(10, 10))
imshow(out, title='unlabeled', ax=ax)
```

bird | dog | bird | horse | cat | truck | monkey | deer
| dog | ship | airplane | horse | airplane | ship | monkey | horse
| deer | horse | car | car | bird | bird | horse | car
| bird | ship | dog | bird | dog | dog | airplane | airplane
| airplane | bird | cat | horse | monkey | car | bird | cat
| bird | horse | bird | cat | monkey | deer | cat | airplane
| horse | monkey | horse | dog | ship | airplane | horse | bird
| cat | horse | ship | car | car | truck | truck | dog



unlabeled



As can be seen from above visualizations, the unlabeled partition contains classes that are not in the training partition. Though not labeled, the unlabeled partition has much more data than the labeled training partition. The large amount of unlabeled label ought to help us learn useful representations. In the next sections, we will use the unlabeled partition to help learn representations that is helpful for downstream tasks.

# Part 1. Autoencoders

We will first build an autoencoder. To keep training time low, we'll use a very simple network structure.

## 1.1 TODO: Build the encoder

Please make sure that your encoder has the same architeture as we print below before your proceed to the decoder part. All conv layers have kernel_size = 4x4, stride=2, padding=1.

### Encoder archiecture

```
        Layer (type)               Output Shape         Param #
            Conv2d-1           [-1, 12, 32, 32]             588
              ReLU-2           [-1, 12, 32, 32]               0
            Conv2d-3           [-1, 24, 16, 16]           4,632
              ReLU-4           [-1, 24, 16, 16]               0
            Conv2d-5             [-1, 48, 8, 8]          18,480
              ReLU-6             [-1, 48, 8, 8]               0
            Conv2d-7             [-1, 24, 4, 4]          18,456
              ReLU-8             [-1, 24, 4, 4]               0
```

Total params: 42,156

Trainable params: 42,156

Non-trainable params: 0

Input size (MB): 0.05 Forward/backward pass size (MB): 0.33

Params size (MB): 0.16

Estimated Total Size (MB): 0.54

In [5]:

```
class Encoder(nn.Module):
    def __init__(self, in_channels=3):
        super(Encoder, self).__init__()

        ##########################################################################
        #                                YOUR CODE HERE
        ##########################################################################
        # TODO: Build an encoder with the architecture as specified above.
        ##########################################################################
        layers = [nn.Conv2d(in_channels, 12, 4, 2, 1),
                  nn.ReLU(),
                  nn.Conv2d(12, 12 * 2, 4, 2, 1),
                  nn.ReLU(),
                  nn.Conv2d(12 * 2, 12 * 4, 4, 2, 1),
                  nn.ReLU(),
                  nn.Conv2d(12 * 4, 12 * 2, 4, 2, 1),
                  nn.ReLU()]
        self.encoder = nn.Sequential(*layers)
        ##########################################################################
        #                                END OF YOUR CODE
        ##########################################################################

    def forward(self, x):
        '''
        Given an image x, return the encoded latent representation h.

        Args:
            x: torch.tensor

        Return:
            h: torch.tensor
        '''

        h = self.encoder(x)

        return h
```

In [6]:

```
# Print out the neural network architectures and activation dimensions.
# Verify that your network has the same architecture as the one we printed abov
encoder = Encoder().to(device)
summary(encoder, [(3, 64, 64)])
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 12, 32, 32]             588
              ReLU-2           [-1, 12, 32, 32]               0
            Conv2d-3           [-1, 24, 16, 16]           4,632
              ReLU-4           [-1, 24, 16, 16]               0
            Conv2d-5             [-1, 48, 8, 8]          18,480
              ReLU-6             [-1, 48, 8, 8]               0
            Conv2d-7             [-1, 24, 4, 4]          18,456
              ReLU-8             [-1, 24, 4, 4]               0
================================================================
Total params: 42,156
Trainable params: 42,156
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.05
Forward/backward pass size (MB): 0.33
Params size (MB): 0.16
Estimated Total Size (MB): 0.54
----------------------------------------------------------------
```

# 1.2 TODO: Build the decoder

Next, we build the decoder to reconstruct the image from the latent representation extracted by the encoder. Please implement the decoder following the architectrue printed here.

---

```
        Layer (type)               Output Shape         Param #
            ConvTranspose2d-1    [-1, 48, 8, 8]          18,480
            ReLU-2               [-1, 48, 8, 8]               0
            ConvTranspose2d-3    [-1, 24, 16, 16]        18,456
            ReLU-4               [-1, 24, 16, 16]             0
            ConvTranspose2d-5    [-1, 12, 32, 32]         4,620
            ReLU-6               [-1, 12, 32, 32]             0
            ConvTranspose2d-7    [-1, 3, 64, 64]            579
            Sigmoid-8            [-1, 3, 64, 64]              0
```

Total params: 42,135
Trainable params: 42,135
Non-trainable params: 0
Input size (MB): 0.00
Forward/backward pass size (MB): 0.52
Params size (MB): 0.16
Estimated Total Size (MB): 0.68

In [7]:

```
class Decoder(nn.Module):
    def __init__(self, out_channels=3, feat_dim=24):
        super(Decoder, self).__init__()

        ##########################################################################
        #                              YOUR CODE HERE
        ##########################################################################
        # TODO: Build the decoder as specified above.
        ##########################################################################
        self.decoder = nn.Sequential(
```

```
            nn.ConvTranspose2d(12 * 2, 12 * 4, 4, 2, 1),
            nn.ReLU(),
            nn.ConvTranspose2d(12 * 4, 12 * 2, 4, 2, 1),
            nn.ReLU(),
            nn.ConvTranspose2d(12 * 2, 12, 4, 2, 1),
            nn.ReLU(),
            nn.ConvTranspose2d(12, out_channels, 4, 2, 1),
            nn.Sigmoid()
        )
        ##########################################################################
        #                                END OF YOUR CODE
        ##########################################################################

    def forward(self, h):
        '''
        Given latent representation h, reconstruct an image patch of size 64 x

        Args:
            h: torch.tensor

        Return:
            x: torch.tensor
        '''
        x = self.decoder(h)
        return x
```

In [8]:

```
# Print out the neural network architectures and activation dimensions.
# Verify that your network has the same architecture as the one we printed abov
decoder = Decoder().to(device)
summary(decoder, [(24, 4, 4)])
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
   ConvTranspose2d-1             [-1, 48, 8, 8]          18,480
              ReLU-2             [-1, 48, 8, 8]               0
   ConvTranspose2d-3           [-1, 24, 16, 16]          18,456
              ReLU-4           [-1, 24, 16, 16]               0
   ConvTranspose2d-5           [-1, 12, 32, 32]           4,620
              ReLU-6           [-1, 12, 32, 32]               0
   ConvTranspose2d-7            [-1, 3, 64, 64]             579
           Sigmoid-8            [-1, 3, 64, 64]               0
================================================================
Total params: 42,135
Trainable params: 42,135
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.52
Params size (MB): 0.16
Estimated Total Size (MB): 0.68
----------------------------------------------------------------
```

## 1.3 Put together the autoencoder

Now we have the encoder and the decoder classes. We only need to implement another `Autoencoder` class to wrap the encoder and the decoder together.

In [9]:

```
class Autoencoder(nn.Module):
    def __init__(self, in_channels=3, feat_dim=64):
        super(Autoencoder, self).__init__()
```

```
        self.encoder = Encoder()
        self.decoder = Decoder()

    def forward(self, x):
        '''
        Compress and reconstruct the input image with encoder and decoder.

        Args:
            x: torch.tensor

        Return:
            x_: torch.tensor
        '''

        h = self.encoder(x)
        x_ = self.decoder(h)

        return x_
```

In [10]:

```
# verify that your aueconder's output size is 3 x 64 x 64
ae = Autoencoder().to(device)
summary(ae, (3, 64, 64))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 12, 32, 32]             588
              ReLU-2           [-1, 12, 32, 32]               0
            Conv2d-3           [-1, 24, 16, 16]           4,632
              ReLU-4           [-1, 24, 16, 16]               0
            Conv2d-5             [-1, 48, 8, 8]          18,480
              ReLU-6             [-1, 48, 8, 8]               0
            Conv2d-7             [-1, 24, 4, 4]          18,456
              ReLU-8             [-1, 24, 4, 4]               0
           Encoder-9             [-1, 24, 4, 4]               0
   ConvTranspose2d-10             [-1, 48, 8, 8]          18,480
             ReLU-11             [-1, 48, 8, 8]               0
   ConvTranspose2d-12           [-1, 24, 16, 16]          18,456
             ReLU-13           [-1, 24, 16, 16]               0
   ConvTranspose2d-14           [-1, 12, 32, 32]           4,620
             ReLU-15           [-1, 12, 32, 32]               0
   ConvTranspose2d-16            [-1, 3, 64, 64]             579
          Sigmoid-17            [-1, 3, 64, 64]               0
          Decoder-18            [-1, 3, 64, 64]               0
================================================================
Total params: 84,291
Trainable params: 84,291
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.05
Forward/backward pass size (MB): 0.95
Params size (MB): 0.32
Estimated Total Size (MB): 1.31
----------------------------------------------------------------
```

## 1.4 TODO: Training the autoencoder

Now, we'll train the autoencoder to reconstruct images from the unlabeled set of STL-10. Note that the reconstructed images will contain significant artifacts, due to the limited size of the bottleneck between the encoder and decoder, and the small network size.

In [11]:
```
# We train on 10,000 unsupervised samples instead of 100,000 samples to speed u
n = 10000
dataset_un_subset, _ = torch.utils.data.random_split(dataset_un, [n,100000-n])
dataloader_un = DataLoader(dataset_un_subset, batch_size=128, shuffle=True)
dataloader_tr = DataLoader(dataset_tr, batch_size=128, shuffle=True)
dataloader_te = DataLoader(dataset_te, batch_size=128, shuffle=False)
```

In [12]:
```
def visualize_recon(model, dataloader):
    '''
    Helper function for visualizing reconstruction performance.

    Randomly sample 8 images and plot the original/reconstructed images.
    '''
    model.eval()
    img = next(iter(dataloader))[0][:8].to(device)
    out = model(img)

    fig, ax = plt.subplots(1, 1, figsize=(15,10))
    inp = torchvision.utils.make_grid(torch.cat((img, out), dim=2), nrow=8)
    imshow(inp.detach().cpu(), ax=ax)
    model.train()
    plt.show()
```

In [13]:
```
def train_ae(model, dataloader, epochs=200):
    '''
    Train autoencoder model.

    Args:
        model: torch.nn.module.
        dataloader: DataLoader. The unlabeled partition of the STL dataset.
    '''

    optimizer = optim.Adam(model.parameters(), lr=1e-3)
    criterion = nn.MSELoss()
    loss_traj = []

    for epoch in tqdm_notebook(range(epochs)):

        loss_epoch = 0
        for x, _ in dataloader:

            ##################################################################
            #                               YOUR CODE HERE
            ##################################################################
            # TODO: Train the autoencoder on one minibatch.
            ##################################################################
            img = x.cuda()

            outputs = model(img)
            loss = criterion(outputs, img)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            ##################################################################
            #                               END OF YOUR CODE
            ##################################################################
            loss_epoch += loss.detach()

        loss_traj.append(loss_epoch)

        if epoch % 10 == 0:
```

```
            print('Epoch {}, loss {:.3f}'.format(epoch, loss_epoch))
            visualize_recon(model, dataloader)

    return model, loss_traj
```

In [14]:

```
# Train the autoencoder for 100 epochs
ae = Autoencoder().to(device)
ae, ae_loss_traj = train_ae(ae, dataloader_un, epochs=100)
torch.save(ae.state_dict(), 'ae.pth')
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:14: TqdmDeprecatio
nWarning: This function will be removed in tqdm==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`


---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-14-3033ca61a8fd> in <module>()
      1 # Train the autoencoder for 100 epochs
      2 ae = Autoencoder().to(device)
----> 3 ae, ae_loss_traj = train_ae(ae, dataloader_un, epochs=100)
      4 torch.save(ae.state_dict(), 'ae.pth')

<ipython-input-13-d1eab64dc993> in train_ae(model, dataloader, epochs)
     22             # TODO: Train the autoencoder on one minibatch.
#
     23             ###########################################################
###################
---> 24             img = x.cuda()
     25 
     26             outputs = model(img)

/usr/local/lib/python3.7/dist-packages/torch/cuda/__init__.py in _lazy_init()
    212         # This function throws if there's a driver initialization erro
r, no GPUs
    213         # are found or any other error occurs
--> 214         torch._C._cuda_init()
    215         # Some of the queued calls may reentrantly call _lazy_init();
    216         # we need to just return without initializing in that case.

RuntimeError: No CUDA GPUs are available
```

After training the autoencoder on the 100,000 images for 100 epochs, we see that autoencoder has leanred to approximately recontruct the image.

# 1.5 TODO: Train a linear classifier

Now, we ask how useful the features are for object recongition. We'll train a linear clasifier that takes the output of the encoder as its features. During training, we freeze the parameters of the encoder. To verify the effectiveness of unsupervised pretraining, we compare the linear classifier accuracy against two baselines:

- Supervised: train the encoder together with the linear classifier on the training set for 100 epochs.
- Random weights: freeze the parameters of a randomly initialized encoder during training.

In [ ]:

```
# Latent representation dimension (the output dimension of the encoder)
feat_dim = 24 * 4 * 4
```

In [ ]:

```
def train_classfier(encoder, cls, dataloader, epochs=100, supervised=False):
    '''
    Args:
        encoder: trained/untrained encoder for unsupervised/supervised training
        cls: linear classifier.
        dataloader: train partition.
        supervised: in supervised mode or not

    Return:
        cls: linear clssifier.
    '''

    optimizer = optim.Adam(cls.parameters(), lr=0.001, weight_decay=1e-4)
    if supervised:
        optimizer = optim.Adam(list(cls.parameters())+list(encoder.parameters()
    criterion = nn.CrossEntropyLoss()
    loss_traj = []
    accuracy_traj = []

    for epoch in tqdm_notebook(range(epochs)):

        loss_epoch = 0
        corrects_epoch = 0
        for x, y in dataloader:

            batch_size = x.size(0)
            x = x.float()
            ####################################################################
            #                               YOUR CODE HERE
            ####################################################################
            # TODO: update the parameters of the classifer. If in supervised mo
            # parameter of the encoder is also updated(already implemented).
            ####################################################################
            x, y = x.to(device), y.to(device)
            img = x
            input = encoder(img)
            input = input.view(batch_size, -1)

            outs = cls(input)
            loss = criterion(outs, y)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            ####################################################################
            #                               END OF YOUR CODE
            ####################################################################
            _, preds = torch.max(outs, 1)
            corrects_epoch += torch.sum(preds == y.data)
            loss_epoch += loss.detach()

        loss_traj.append(loss_epoch)
        epoch_acc = corrects_epoch.double() / len(dataloader.dataset)
        accuracy_traj.append(epoch_acc)

        if epoch % 10 == 0:
            print('Epoch {}, loss {:.3f}, train accuracy {}'.format(epoch, loss

    return cls, loss_traj
```

In [ ]:

```
def test(encoder, cls, dataloader):
    '''
```

```
    Calculate the accuracy of the trained linear classifier on the test set.
    '''
    cls.eval()

    loss_epoch = 0
    corrects_epoch = 0
    for x, y in dataloader:

        x = x.float()
        batch_size = x.size(0)
        x, y = x.to(device), y.to(device)
        h = encoder(x).view(batch_size, -1)
        outs = cls(h)
        _, preds = torch.max(outs, 1)
        corrects_epoch += torch.sum(preds == y.data)

    epoch_acc = corrects_epoch.double() / len(dataloader.dataset)
    print('Test accuracy {}'.format(epoch_acc))
```

In [ ]:

```
# Method I: unsupervised pretraining + training linear classifier
# Freeze the parameters of the trained autoencoder
# Train a linear classifier using the features
###TODO: Set the value of supervised parameter in train_classfier###
linear_cls = nn.Sequential(nn.Linear(feat_dim, 10)).to(device)
cls_unsupervised, loss_traj_unsupervised = train_classfier(ae.encoder, linear_c
test(ae.encoder, cls_unsupervised, dataloader_te)
```

In [ ]:

```
# Method II: supervised training
# Train the encoder together with the linear classifier
###TODO: Set the value of supervised parameter in train_classfier###
linear_cls = nn.Sequential(nn.Linear(feat_dim, 10)).to(device)
encoder = Autoencoder().to(device).encoder
cls_supervised, loss_traj_supervised = train_classfier(encoder, linear_cls, dat
test(encoder, cls_supervised, dataloader_te)
```

In [ ]:

```
# Method III: random encoder + training linear classifier
# We freeze the parameters of the randomly initialized encoder during training
###TODO: Set the value of supervised parameter in train_classfier###
linear_cls = nn.Sequential(nn.Linear(feat_dim, 10)).to(device)
encoder = Autoencoder().to(device).encoder
cls_random, loss_traj_random = train_classfier(encoder, linear_cls, dataloader_
test(encoder, cls_random, dataloader_te)
```

With pretrained encoder, the linear classifier should achieve about 30% accuracy on the test set. With the supervised approach, the linear classifier should achieve an accuracy above 40%. The random encoder approach performs the worse among these three. The observation that the pretrained encoder outperforms the random encoder confirms that unsupervised pretraining has learned a useful represenation. However, the quality of this learned representation is not good because it only performs slightly better than the random encoder. In the next part, we'll explore contrastive multiview coding, which learns a more useful representation than the autoencoder.

In [ ]:

```
del dataset_un
del dataset_te
del dataset_tr
```

# Part 2. Contrastive Multiview Coding

In this part, we will implement contrastive multi-view coding (CMC). This is a variation of the contrastive representation learning method we discussed in class. We'll learn a vector representation for images: in this representation, two artificially corrupted versions of a given image should have a large dot product, while dot products of two different images should have a small dot product. In contrastive multiview coding, these corruptions are "views" of an image that contain complementary information (e.g. color and grayscale values). A good representation should create similar vectors for these two views.

The contrastive learning objective function can be expressed as:

$$h_\theta\left(\{v_1, v_2\}\right) = \exp\left(\frac{f_{\theta_1}\left(v_1\right) \cdot f_{\theta_2}\left(v_2\right)}{\left\|f_{\theta_1}\left(v_1\right)\right\| \cdot \left\|f_{\theta_2}\left(v_2\right)\right\|} \cdot \frac{1}{\tau}\right),$$

where $f_{\theta_1}$ and $f_{\theta_2}$ are encoders for extracting representations from view 1 and view 2, respectively, and $\tau$ is the temperature hyperparameter for controlling the range of the exponential score.

We'll make the loss treat the two views the same by adding two versions of the loss together: $\mathcal{L}_{\text{contrast}}^{V_1,V_2}$ and $\mathcal{L}_{\text{contrast}}^{V_2,V_1}$, i.e.,

$$\mathcal{L}\left(V_1, V_2\right) = \mathcal{L}_{\text{contrast}}^{V_1,V_2} + \mathcal{L}_{\text{contrast}}^{V_2,V_1}.$$

We will implement CMC on $Lab$ image color space. Like the familiar RGB color space, Lab iamges have three channels. Channel $L$ corresponds to the *luminance* of the image and channels $ab$ corresponds to the *chrominance* of the image. During contrastive training, $L$ channel and $ab$ channels will be processed by two encoders separately.

In [ ]:

```
# color space transfrom
from skimage import color

class RGB2Lab(object):
    """Convert RGB PIL image to ndarray Lab."""
    def __call__(self, img):
        img = np.asarray(img, np.uint8)
        img = color.rgb2lab(img)
        return img
```

In [ ]:

```
# Visualize the Lab color channels.

original = dataloader_te.dataset[4][0].numpy().transpose((1,2,0))
lab = color.rgb2lab(original)
print('Lab color image size {}'.format(lab.shape))

def extract_single_dim_from_LAB_convert_to_RGB(image,idim):
    '''
    image is a single lab image of shape (None,None,3)
    '''
    z = np.zeros(image.shape)
    if idim != 0 :
        z[:,:,0]=80 ## need brightness to plot the image along 1st or 2nd axis
    z[:,:,idim] = image[:,:,idim]
    z = color.lab2rgb(z)
    return(z)
```

```
fig, ax = plt.subplots(1, 4, figsize=(15,10))
lab_rgb_gray = extract_single_dim_from_LAB_convert_to_RGB(lab,0)
ax[0].imshow(lab_rgb_gray); ax[0].axis("off")
ax[0].set_title("L: Luminance")

lab_rgb_gray = extract_single_dim_from_LAB_convert_to_RGB(lab,1)
ax[1].imshow(lab_rgb_gray); ax[1].axis("off")
ax[1].set_title("A: green to red")

lab_rgb_gray = extract_single_dim_from_LAB_convert_to_RGB(lab,2)
ax[2].imshow(lab_rgb_gray); ax[2].axis("off")
ax[2].set_title("B: blue to yellow")

ax[3].imshow(original); ax[3].axis("off")
ax[3].set_title("Original RGB image")
plt.show()
```

We modify the __getitem__ method of PyTorch STL-10 Dataset class so that it returns the index of the returned image. The index will be used later in the contrastive learning to form positive/negative training pairs.

In [ ]:

```
# This part can be ignored.

from __future__ import print_function
from PIL import Image
import os
import os.path
import numpy as np

from torchvision.datasets.vision import VisionDataset
from torchvision.datasets.utils import check_integrity, download_and_extract_ar

class STL10_CMC(VisionDataset):
    """`STL10 <https://cs.stanford.edu/~acoates/stl10/>`_ Dataset.
    Args:
        root (string): Root directory of dataset where directory
            ``stl10_binary`` exists.
        split (string): One of {'train', 'test', 'unlabeled', 'train+unlabeled'
            Accordingly dataset is selected.
        folds (int, optional): One of {0-9} or None.
            For training, loads one of the 10 pre-defined folds of 1k samples f
             standard evaluation procedure. If no value is passed, loads the 5k
        transform (callable, optional): A function/transform that  takes in an
            and returns a transformed version. E.g, ``transforms.RandomCrop``
        target_transform (callable, optional): A function/transform that takes
            target and transforms it.
        download (bool, optional): If true, downloads the dataset from the inte
            puts it in root directory. If dataset is already downloaded, it is
            downloaded again.
    """
    base_folder = 'stl10_binary'
    url = "http://ai.stanford.edu/~acoates/stl10/stl10_binary.tar.gz"
    filename = "stl10_binary.tar.gz"
    tgz_md5 = '91f7769df0f17e558f3565bffb0c7dfb'
    class_names_file = 'class_names.txt'
    folds_list_file = 'fold_indices.txt'
    train_list = [
        ['train_X.bin', '918c2871b30a85fa023e0c44e0bee87f'],
        ['train_y.bin', '5a34089d4802c674881badbb80307741'],
        ['unlabeled_X.bin', '5242ba1fed5e4be9e1e742405eb56ca4']
    ]

    test_list = [
```

```python
        ['test_X.bin', '7f263ba9f9e0b06b93213547f721ac82'],
        ['test_y.bin', '36f9794fa4beb8a2c72628de14fa638e']
    ]
    splits = ('train', 'train+unlabeled', 'unlabeled', 'test')

    def __init__(self, root, split='train', folds=None, transform=None,
                 target_transform=None, download=False):
        super(STL10_CMC, self).__init__(root, transform=transform,
                                        target_transform=target_transform)
        self.split = verify_str_arg(split, "split", self.splits)
        self.folds = self._verify_folds(folds)

        if download:
            self.download()
        elif not self._check_integrity():
            raise RuntimeError(
                'Dataset not found or corrupted. '
                'You can use download=True to download it')

        # now load the picked numpy arrays
        if self.split == 'train':
            self.data, self.labels = self.__loadfile(
                self.train_list[0][0], self.train_list[1][0])
            self.__load_folds(folds)

        elif self.split == 'train+unlabeled':
            self.data, self.labels = self.__loadfile(
                self.train_list[0][0], self.train_list[1][0])
            self.__load_folds(folds)
            unlabeled_data, _ = self.__loadfile(self.train_list[2][0])
            self.data = np.concatenate((self.data, unlabeled_data))
            self.labels = np.concatenate(
                (self.labels, np.asarray([-1] * unlabeled_data.shape[0])))

        elif self.split == 'unlabeled':
            self.data, _ = self.__loadfile(self.train_list[2][0])
            self.labels = np.asarray([-1] * self.data.shape[0])
        else:  # self.split == 'test':
            self.data, self.labels = self.__loadfile(
                self.test_list[0][0], self.test_list[1][0])

        class_file = os.path.join(
            self.root, self.base_folder, self.class_names_file)
        if os.path.isfile(class_file):
            with open(class_file) as f:
                self.classes = f.read().splitlines()

    def _verify_folds(self, folds):
        if folds is None:
            return folds
        elif isinstance(folds, int):
            if folds in range(10):
                return folds
            msg = ("Value for argument folds should be in the range [0, 10), "
                   "but got {}.")
            raise ValueError(msg.format(folds))
        else:
            msg = "Expected type None or int for argument folds, but got type {
            raise ValueError(msg.format(type(folds)))

    def __getitem__(self, index):
        """
        Args:
            index (int): Index
        Returns:
```

```python
            tuple: (image, target) where target is index of the target class.
        """
        if self.labels is not None:
            img, target = self.data[index], int(self.labels[index])
        else:
            img, target = self.data[index], None

        # doing this so that it is consistent with all other datasets
        # to return a PIL Image
        img = Image.fromarray(np.transpose(img, (1, 2, 0)))

        if self.transform is not None:
            img = self.transform(img)

        if self.target_transform is not None:
            target = self.target_transform(target)

        return img, target, index

    def __len__(self):
        return self.data.shape[0]

    def __loadfile(self, data_file, labels_file=None):
        labels = None
        if labels_file:
            path_to_labels = os.path.join(
                self.root, self.base_folder, labels_file)
            with open(path_to_labels, 'rb') as f:
                labels = np.fromfile(f, dtype=np.uint8) - 1  # 0-based

        path_to_data = os.path.join(self.root, self.base_folder, data_file)
        with open(path_to_data, 'rb') as f:
            # read whole file in uint8 chunks
            everything = np.fromfile(f, dtype=np.uint8)
            images = np.reshape(everything, (-1, 3, 96, 96))
            images = np.transpose(images, (0, 1, 3, 2))

        return images, labels

    def _check_integrity(self):
        root = self.root
        for fentry in (self.train_list + self.test_list):
            filename, md5 = fentry[0], fentry[1]
            fpath = os.path.join(root, self.base_folder, filename)
            if not check_integrity(fpath, md5):
                return False
        return True

    def download(self):
        if self._check_integrity():
            print('Files already downloaded and verified')
            return
        download_and_extract_archive(self.url, self.root, filename=self.filenam
        self._check_integrity()

    def extra_repr(self):
        return "Split: {split}".format(**self.__dict__)

    def __load_folds(self, folds):
        # loads one of the folds if specified
        if folds is None:
            return
        path_to_folds = os.path.join(
            self.root, self.base_folder, self.folds_list_file)
        with open(path_to_folds, 'r') as f:
```

```
            str_idx = f.read().splitlines()[folds]
            list_idx = np.fromstring(str_idx, dtype=np.uint8, sep=' ')
            self.data, self.labels = self.data[list_idx, :, :, :], self.labels[
```

In [ ]:

```
# Add RGB2Lab color space transform to the dataloader.
color_transfer = RGB2Lab()
unlabeled_transform = transforms.Compose([transforms.RandomHorizontalFlip(),
                                          transforms.RandomCrop(64),
                                          color_transfer,
                                          transforms.ToTensor()])

labeled_transform = transforms.Compose([transforms.CenterCrop(64),
                                        color_transfer,
                                        transforms.ToTensor()])


# We use the PyTorch built-in class to download the STL-10 dataset.
# The 'unlabeled' partition contains 100,000 images without labels.
# It's used for leanring representations with unsupervised learning.
dataset_un = STL10_CMC('./data', 'unlabeled', download=True, transform=unlabele

dataset_tr = torchvision.datasets.STL10('./data', 'train', download=False, tran
dataset_te = torchvision.datasets.STL10('./data', 'test', download=False, trans
```

# 2.1 TODO: Build CMC Encoders

We use two encoders for CMC. One for extracting representations from L channel, another is used for extracting representations from ab channels. For a fair comparison, we use the same encoder architecture we built in Part 1.

In [ ]:

```
feat_dim = 24 * 4 * 4
```

In [ ]:

```
class EncoderCMC(nn.Module):
    def __init__(self):
        super(EncoderCMC, self).__init__()

        self.l_encoder = Encoder(in_channels=1)
        self.ab_encoder = Encoder(in_channels=2)

    def forward(self, x):
        '''
        Extract features from L and ab channels.

        Args:
            x: torch.tensor

        Returns:
            feat_l: torch.tensor, (-1, feat_dim)
            feat_ab: torch.tensor, (-1, feat_dim)
        '''

        ###################################################################
        #                          YOUR CODE HERE
        ###################################################################
        # TODO: apply l_encoder and ab_encoder to the L channel and ab channels
        # the input image x. You can first split x according to channels. Then
        # l_encoder and ab_encoder independently to corresponding channels.
        ###################################################################
        l_ab = torch.split(x, [1, 2], 1)
```

```
        feat_l = self.l_encoder(l_ab[0])
        feat_l = torch.reshape(feat_l, (feat_l.shape[0], feat_dim))

        feat_ab = self.ab_encoder(l_ab[1])
        feat_ab = torch.reshape(feat_ab, (feat_ab.shape[0], feat_dim))
        ########################################################################
        #                                END OF YOUR CODE
        ########################################################################
        return feat_l, feat_ab
```

In [ ]:

```
encoder_cmc = EncoderCMC().to(device)
img = torch.rand(128, 3, 64, 64).cuda()
feat_l, feat_ab = encoder_cmc(img)
assert feat_l.size() == (128, feat_dim), "L feature has wrong dimension"
assert feat_ab.size() == (128, feat_dim), "ab feature has wrong dimension"
```

## 2.2 TODO: Implement the CMC loss

As the first step, we compute $\log h_\theta\left(\{v_1, v_2\}\right)$ which is the normalized dot product between the L features and ab features for postive and negative pairs i.e.,

$$\log h_\theta\left(\{v_1, v_2\}\right) = \frac{f_{\theta_1}\left(v_1\right) \cdot f_{\theta_2}\left(v_2\right)}{\left\|f_{\theta_1}\left(v_1\right)\right\| \cdot \left\|f_{\theta_2}\left(v_2\right)\right\|} \cdot \frac{1}{\tau}.$$

See TODO block for more description.

In [ ]:

```
import math
class CMCScore(nn.Module):
    '''
    Calculate hθ({v1,v2}) and hθ({v2,v1}).

    To efficiently compute the scores, we use memories to store L and ab
    representations. For more details on this, please refer to the original
    CMC paper
    '''

    def __init__(self, feat_dim, N, K, T=0.1, momentum=0.5):
        '''
        Args:
            feat_dim: int, dimension of the extracted representations
            N: int, number of samples in the dataset.
            K: int, number of negative examples.
            T: float, temeprature.
            momentum: float. momentum of memory.
        '''
        super(CMCScore, self).__init__()
        self.N = N
        self.K = K
        self.feat_dim = feat_dim
        self.ones = torch.ones(N).cuda()
        self.eps = 1e-7

        self.register_buffer('params', torch.tensor([K, T, momentum]))
        stdv = 1. / math.sqrt(feat_dim / 3)
        self.register_buffer('memory_l', torch.rand(N, feat_dim).mul_(2 * stdv)
        self.register_buffer('memory_ab', torch.rand(N, feat_dim).mul_(2 * stdv

    def forward(self, l, ab, y, idx=None):
        '''
```

```
        Args:
            l: torch.tensor. l channel representation. (-1, feat_dim)
            ab: torch.tensor. ab channel representation. (-1, feat_dim)
            y: torch.tensor. Dataset index corresponding to the input images.

        Returns:
            out_l: torch.tensor. (-1, K+1, 1)
            out_ab: torch.tensor. (-1, K+1, 1)
        '''
        K = int(self.params[0].item())
        T = self.params[1].item()

        momentum = self.params[2].item()
        batch_size = l.size(0)
        N = self.N
        feat_dim = self.feat_dim

        # normalize l and ab representations
        l = l / (l.pow(2).sum(dim=1, keepdim=True).sqrt() + self.eps)
        ab = ab / (ab.pow(2).sum(dim=1, keepdim=True).sqrt() + self.eps)

        # Randomly sample K indicies for each anchor data to form negative pair
        if idx is None:
            idx = torch.multinomial(self.ones, batch_size*(self.K+1), replaceme
            idx = idx.view(batch_size, -1)
            # set the 0-th element to be positive sample.
            idx.select(1, 0).copy_(y.data)

        ########################################################################
        #                                 YOUR CODE HERE
        ########################################################################
        # TODO: Compute out_l and out_ab. out_l is the normalized dot product b
        # anchor l channel and randomly sampled ab channels. out_ab is the oppo
        # Using the stored representations from the memory to avoid computing n
        # representations on-the-fly. Make sure you use the idx varaible we cre
        # above to retrieve representations from the memory.
        ########################################################################
        # # L channel anchor
        weight_ab = torch.index_select(self.memory_ab, 0, idx.view(-1)).detach(
        weight_ab = weight_ab.view(batch_size, K + 1, feat_dim)
        out_l = torch.bmm(weight_ab, l.view(batch_size, feat_dim, 1))

        # # AB channel anchor
        weight_l = torch.index_select(self.memory_l, 0, idx.view(-1)).detach()
        weight_l = weight_l.view(batch_size, K + 1, feat_dim)
        out_ab = torch.bmm(weight_l, ab.view(batch_size, feat_dim, 1))
        ########################################################################
        #                                 IMPORTANT
        ########################################################################
        out_l = out_l.contiguous()
        out_ab = out_ab.contiguous()

        # # update memory
        with torch.no_grad():
            l_pos = torch.index_select(self.memory_l, 0, y.view(-1))
            l_pos.mul_(momentum)
            l_pos.add_(torch.mul(l, 1 - momentum))
            l_norm = l_pos.pow(2).sum(1, keepdim=True).pow(0.5)
            updated_l = l_pos.div(l_norm)
            self.memory_l.index_copy_(0, y, updated_l)

            ab_pos = torch.index_select(self.memory_ab, 0, y.view(-1))
            ab_pos.mul_(momentum)
            ab_pos.add_(torch.mul(ab, 1 - momentum))
            ab_norm = ab_pos.pow(2).sum(1, keepdim=True).pow(0.5)
```

```
            updated_ab = ab_pos.div(ab_norm)
            self.memory_ab.index_copy_(0, y, updated_ab)

        return out_l, out_ab
```

In [ ]:

```
# sanity check
K = 256
contrast = CMCScore(feat_dim, 20000, K).cuda()
y = torch.randint(low=0, high=5000, size=(128,)).cuda()
out_l, out_ab = contrast(feat_l, feat_ab, y)
assert out_l.size() == (128, K+1, 1), "L scores have wrong dimension"
assert out_ab.size() == (128, K+1, 1), "ab scores have wrong dimension"
```

Next, we compute the softmax loss $\mathcal{L}^{V_1,V_2}_{\text{contrast}}$ and $\mathcal{L}^{V_2,V_1}_{\text{contrast}}$.

In [ ]:

```
class SoftmaxLoss(nn.Module):
    """
    Softmax cross-entropy loss.
    """
    def __init__(self):
        super(SoftmaxLoss, self).__init__()
        self.criterion = nn.CrossEntropyLoss()

    def forward(self, x):

        batch_size = x.shape[0]
        x = x.squeeze()

        ########################################################################
        #                               YOUR CODE HERE
        ########################################################################
        # TODO: compute loss values. Note that you need to provide label to
        # CrossEntropyLoss(Hint: the positive sample is always the first one).
        # You also want your label is long type.
        ########################################################################
        label = torch.zeros([batch_size]).cuda().long()
        loss = self.criterion(x, label)
        ########################################################################
        #                               END OF YOUR CODE
        ########################################################################

        return loss
```

In [ ]:

```
criterion_l = SoftmaxLoss().cuda()
criterion_ab = SoftmaxLoss().cuda()

# make sure the loss values are scalars
criterion_l(out_l), criterion_ab(out_ab)
```

## 2.3 TODO: Contrastive Multiview Training

Train L and ab encoders using the CMC loss fuction.

In [ ]:

```
def train_cmc(model, contrast, criterion_l, criterion_ab, dataloader, epochs=10

    optimizer = optim.Adam(model.parameters(), lr=1e-3, betas=(0.5, 0.999))

    for epoch in tqdm_notebook(range(epochs)):
```

```
        model.train()
        ab_prob_epoch = 0
        l_prob_epoch = 0
        loss_epoch = 0
        for idx, (inputs, _, index) in enumerate(dataloader):

            batch_size = inputs.size(0)
            inputs = inputs.float().to(device)
            index = index.to(device)

            ###################################################################
            #                                YOUR CODE HERE
            ###################################################################
            # TODO: compute loss values and train CMC Encoders. Note that you n
            # provide label to CrossEntropyLoss. (Hint: the positive sample is
            # the first one).
            ###################################################################
            feat_l, feat_ab = model(inputs)
            out_l, out_ab = contrast(feat_l, feat_ab, index)

            l_loss = criterion_l(out_l)
            ab_loss = criterion_l(out_ab)
            loss = l_loss + ab_loss

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            ###################################################################
            #                                END OF YOUR CODE
            ###################################################################

            l_prob = F.softmax(out_l, dim=1)[:, 0, 0].sum().detach().cpu()
            ab_prob = F.softmax(out_ab, dim=1)[:, 0, 0].sum().detach().cpu()

            l_prob_epoch += l_prob
            ab_prob_epoch += ab_prob
            loss_epoch += loss.data

        l_prob_epoch = l_prob_epoch / len(dataloader.dataset)
        ab_prob_epoch = ab_prob_epoch / len(dataloader.dataset)
        loss_epoch = loss_epoch / len(dataloader)

        print('Epoch {}, loss {:.3f}\t'
              'avg prob for L channel {:.3f}\t'
              'avg prob for ab channels {:.3f}'.format(
                  epoch, loss_epoch, l_prob_epoch, ab_prob_epoch))

    return model
```

In [ ]:

```
K = 256 # number of negative pairs
n = 10000
dataset_un_subset, _ = torch.utils.data.random_split(dataset_un, [n,100000-n])
dataloader_un_cmc = DataLoader(dataset_un_subset, batch_size=128, shuffle=True,
contrast = CMCScore(feat_dim, 100000, K).cuda()

###############################################################################
#                        UNCOMMENT FOR DEBUGGING                              #
###############################################################################
# Uncomment these lines when debugging. It trains the CMC model on a subset of
# STL-10 ublabeled. Make sure the loss value decreases and the average matching
# probablity increases over training.

# n = 2000
```

```
# dataset_debug, _ = torch.utils.data.random_split(dataset_un, [n,100000-n])
# dataloader_un_cmc = DataLoader(dataset_debug, batch_size=128, shuffle=True)

##############################################################################
#                         UNCOMMENT FOR DEBUGGING                            #
##############################################################################

# Training will take 30 mins.
encoder_cmc = EncoderCMC().to(device)
encoder_cmc = train_cmc(encoder_cmc, contrast, criterion_l, criterion_ab, datal
torch.save(encoder_cmc.state_dict(), 'encoder_cmc.pth')
```

## 2.4 Train a linear classifier

Train a linear classifier on top of the CMC representations.

In [ ]:

```
class EncoderCMC_Cat(nn.Module):
    '''
    Wraper class for EncoderCMC. Concatenate feat_l and feat_ab to form a singl
    representation vector. This enables us to reuse the train_classifier routin
    '''
    def __init__(self, model):
        super(EncoderCMC_Cat, self).__init__()
        self.model = model

    def forward(self, x):
        feat_l, feat_ab = self.model(x)
        return torch.cat((feat_l, feat_ab), dim=1)
```

In [ ]:

```
dataloader_tr = DataLoader(dataset_tr, batch_size=128, shuffle=True, num_worker
dataloader_te = DataLoader(dataset_te, batch_size=128, shuffle=False, num_worke
```

In [ ]:

```
encoder_cmc_cat = EncoderCMC_Cat(encoder_cmc)

linear_cls = nn.Sequential(nn.Linear(feat_dim*2, 10)).to(device)
cls_cmc, loss_traj_cmc = train_classfier(encoder_cmc_cat, linear_cls, dataloade
test(encoder_cmc_cat, cls_cmc, dataloader_te)
```

# TODO: Report results

Please report the test accuracy of all four linear classifiers below.

### Autoencoder-based

method 1 accuracy: 0.34275

method 2 accuracy: 0.44

method 3 accuracy: 0.332625

### CMC

accuracy: 0.43822

# Summary

So far, we have trained linear classifiers on top of autoencoder representations and CMC representations.

With CMC, we learn a more useful representation than autoencoder. In the paper, the authors also implemented a more effective loss function based on Noise Contrastive Estimation (NCE). You are encouraged to implement NCE and compare its performance with our (K+1)-way Softmax loss function.

# Convert to PDF

In [ ]:

```
# generate pdf
# %%capture
!git clone https://gist.github.com/bc5f1add34fef7c7f9fb83d3783311e2.git
!cp bc5f1add34fef7c7f9fb83d3783311e2/colab_pdf.py colab_pdf.py
from colab_pdf import colab_pdf
# change the name to your ipynb file name shown on the top left of Colab window
# Important: make sure that your file name does not contain spaces!
colab_pdf('Starter_PS8_Representation_Learning.ipynb')
```

If the above cell doesn't work, try this alternative.