

ex10_2

July 13, 2019

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In [3]: from sklearn.manifold import TSNE
        from sklearn.cluster import KMeans
        import numpy as np
        import matplotlib.pyplot as plt
        import torch.nn as nn
        import torch
        from torch.nn import functional as F
        from torch.autograd import Variable
        from torch.utils.data import DataLoader
        from torchvision import datasets

        import torch.distributions as tdist
        import torchvision.transforms as transforms

class Variational_Autoencoder(nn.Module):

    def __init__(self, input_shape=(28, 28, 1)):
        super(Variational_Autoencoder, self).__init__()
        self.training = True
        ndist = tdist.Normal(torch.tensor([4.0]), torch.tensor([0.5]))
        self.encoder = nn.Sequential(
            nn.Linear(input_shape[0]*input_shape[1]*input_shape[2], 512),
            nn.ReLU(),
            nn.Linear(512, 256),
            nn.ReLU(),
            nn.Linear(256, 64)
        )

        self.decoder = nn.Sequential(
            nn.Linear(64, 256),
            nn.ReLU(),
            nn.Linear(256, 512),
            nn.ReLU(),
            nn.Linear(512, input_shape[0]*input_shape[1]*input_shape[2]),
            nn.Tanh()
        )
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def forward(self, x=None, decode=None):
    if decode is None:
        flat = torch.flatten(x, start_dim=2)
        features = self.encoder(flat)

        # get mean and std-dev
        mu = torch.mean(features, dim=2)
        sig = torch.std(features, dim=2)
        # make sure bit have the same number of elements as out
        sigmas = torch.ones((features.shape[0], features.shape[2]))*sig
        means = torch.ones((features.shape[0], features.shape[2]))*mu

        dist = reparameterize(self, means, sigmas)

        out = self.decoder(dist)

        return out, means, sigmas, features
    return self.decoder(decode)

# Manifold approximation using tSNE
#
# features: (numpy array) N x D feature matrix
# images: (numpy array) N x H x W x 3
# path_save: string (path where you want to save the final image)
def apply_tnse_img(features, images, path_save='./tsne_img.png'):

    tnse = TSNE(n_components=2, init='pca', n_iter=1000, random_state=1254, perplexity=
    # np.set_printoptions(False)
    vis_data = tnse.fit_transform(features)
    vis_x = vis_data[:, 0]
    vis_y = vis_data[:, 1]

    # get max heigth, width
    max_width = max([image.shape[0] for image in images])
    max_height = max([image.shape[1] for image in images])

    # get max, min coords
    x_min, x_max = vis_x.min(), vis_x.max()
    y_min, y_max = vis_y.min(), vis_y.max()

    # Fix the ratios
    res = 700
    sx = (x_max - x_min)
    sy = (y_max - y_min)
    if sx > sy:
        res_x = int(sx / float(sy) * res)
        res_y = res
    else:

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        res_x = res
        res_y = int(sy / float(sx) * res)

    # impaint images
    canvas = np.ones((res_x + max_width, res_y + max_height, 3))
    x_coords = np.linspace(x_min, x_max, res_x)
    y_coords = np.linspace(y_min, y_max, res_y)
    for x, y, image in zip(vis_x, vis_y, images):
        w, h = image.shape[:2]
        x_idx = np.argmin((x - x_coords) ** 2)
        y_idx = np.argmin((y - y_coords) ** 2)
        try:
            canvas[x_idx:x_idx + w, y_idx:y_idx + h] = image
        except:
            print('Image out of borders.... skip!')

    # plot image
    fig = plt.figure()
    plt.imshow(canvas)

    mng = plt.get_current_fig_manager()
    mng.full_screen_toggle()
    plt.show()
    plt.pause(3)
    fig.savefig(path_save, bbox_inches='tight')

# Reparametrization trick for training VAEs
#
# mu and logvar: output of your encoder
def reparameterize(self, mu, logvar):
    if self.training:
        std = logvar.mul(0.5).exp_()
        eps = Variable(std.data.new(std.size()).normal_())
        return eps.mul(std).add_(mu)
    else:
        return mu

# VAE Loss
#
# recon_x: image reconstructions
# x: images
# mu and logvar: outputs of your encoder
# batch_size: batch_size
# img_size: width, respectively height of you images
# nc: number of image channels
def loss_function(recon_x, x, mu, logvar, batch_size, img_size, nc):
    MSE = F.mse_loss(recon_x, x.view(-1, img_size * img_size * nc))

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    #  $0.5 * \sum(1 + \log(\sigma^2) - \mu^2 - \sigma^2)$ 
    KLD = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())

    # Normalize
    KLD /= batch_size * img_size * img_size * nc

    return MSE + KLD

def train(trainloader, model, batchsize, use_gpu=False, lr=0.001, num_epochs = 10):
    model.train()
    optimizer = torch.optim.Adam(model.parameters(), lr=lr)

    if use_gpu:
        model.cuda()

    for epoch in range(num_epochs):
        for step, (x, label) in enumerate(trainloader):
            if use_gpu:
                x = x.cuda()
            optimizer.zero_grad()
            recon_x, mu, sigma, features = model(x=x)
            loss = loss_function(recon_x, x, mu, sigma, batchsize, 28, 1)
            loss.backward()
            optimizer.step()

            if epoch == 1 or epoch == 5:
                if step == 0:
                    means = torch.zeros((10, 64))
                    sigmas = torch.ones((10, 64))
                    newCode = torch.normal(means, sigmas)
                    newImg = model(decode=newCode)
                    plt.figure()
                    for i in range(10):
                        plt.subplot(3, 10, i*3 + 1)
                        plt.imshow(recon_x[i].view(28, 28).detach().numpy());plt.title('recon')
                        plt.subplot(3, 10, i * 3 + 2)
                        plt.imshow(x[i].view(28, 28).detach().numpy());plt.title('x');
                        plt.subplot(3, 10, i * 3 + 3)
                        plt.imshow(newImg[i].view(28, 28).detach().numpy());plt.title('new')
                    plt.show()

                means = torch.zeros((10, 64))
                sigmas = torch.ones((10, 64))
                newCode = torch.normal(means, sigmas)
                newImg = model(decode=newCode)
                plt.figure()
                for i in range(10):
                    plt.subplot(3, 10, i * 3 + 1)

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plt.imshow(recon_x[i].view(28, 28).detach().numpy());plt.title('rec');plt.axis(
plt.subplot(3, 10, i * 3 + 2)
plt.imshow(x[i].view(28, 28).detach().numpy());plt.title('x');plt.axis('off')
plt.subplot(3, 10, i * 3 + 3)
plt.imshow(newImg[i].view(28, 28).detach().numpy());plt.title('new');plt.axis(
plt.show()

def visualizeDataManifold(loader, model, batchsize, use_gpu=False):
    model.eval()
    if use_gpu:
        model.cuda()

    for x, label in loader:
        break;
    if use_gpu:
        x = x.cuda()
    recon_x, mu, sig, features = model(x=x)
    flat = torch.flatten(x, start_dim=2)
    flat = flat.squeeze(1)
    kmeans = KMeans(n_clusters=10).fit(flat.detach().numpy())
    pred = kmeans.predict(flat.detach().numpy())
    apply_tnse_img(features.squeeze(1).detach().numpy(), x.squeeze(1).detach().numpy())

if __name__ == '__main__':
    load = False
    tr = True
    evl = True
    model = Variational_Autoencoder()

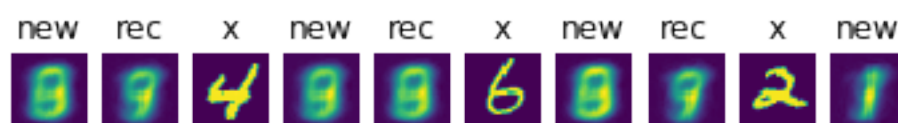
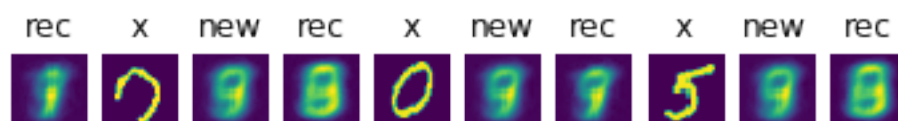
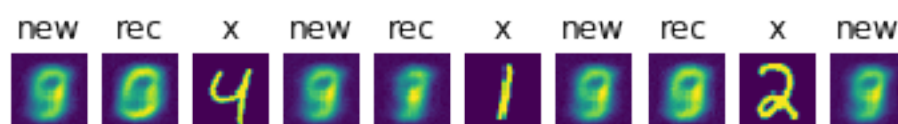
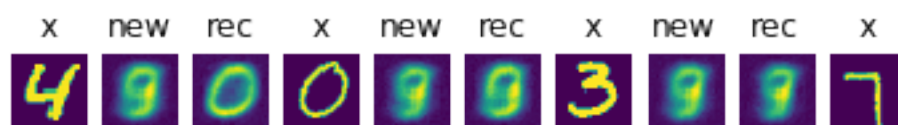
    if load:
        model.load_state_dict(torch.load('./s_dict2.pt'))

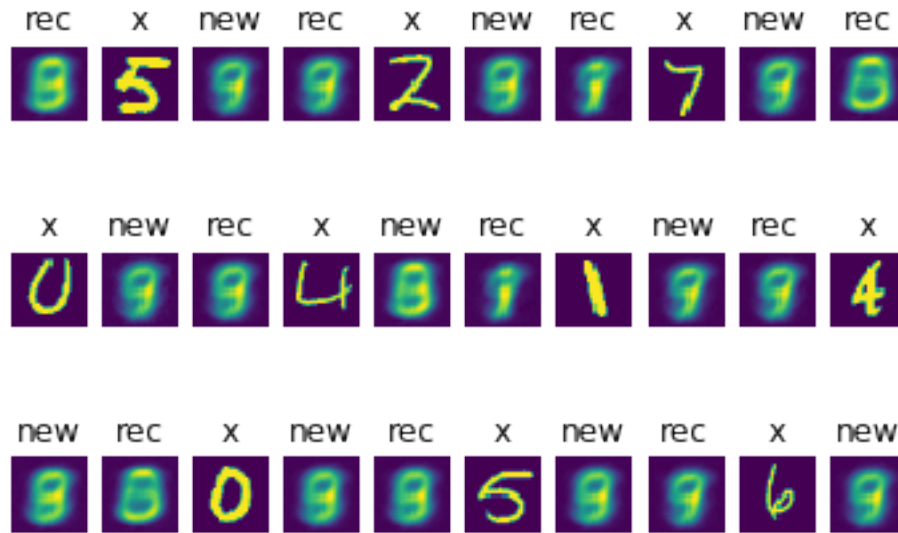
    if tr:
        transform = transforms.ToTensor()
        trainset = datasets.MNIST('.', transform=transform)
        trainloader = torch.utils.data.DataLoader(trainset, batch_size=128, pin_memory=
        train(trainloader, model, 128)

        torch.save(model.state_dict(), './s_dict2.pt')

    if evl:
        transform = transforms.ToTensor()
        dset = datasets.MNIST('.', transform=transform)
        loader = torch.utils.data.DataLoader(dset, batch_size=400, pin_memory=True, num
        visualizeDataManifold(loader, model, 400)

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[illegible]

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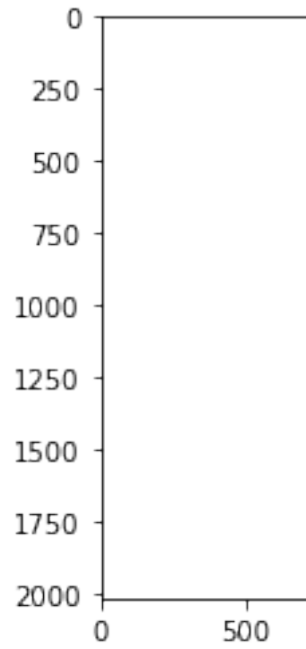
[illegible]

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Comments: I think the image was too large to be visualized. At least that's what the warnings said. I guess that the result is, that on the 2D plane most features map to one of the 10 image classes.