Compare_AE_Collections_StaticPlot

March 31, 2021

[1]:

```
%matplotlib inline
import os, sys
import numpy as np
import pickle
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision
import torch.distributions as torchD

import torch, seaborn as sns
import pandas as pd

from mpl_toolkits.mplot3d import Axes3D
from matplotlib.colors import ListedColormap

from utils import *
from AE_collection import *
```

0.1 Load Dataset

[2]:

```
# !wget www.di.ens.fr/~lelarge/MNIST.tar.gz
# !tar -zxvf MNIST.tar.gz
```

[3]:

```
batch_size = 128

transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor()])

train_dataset = torchvision.datasets.MNIST(
    root="../data/", train=True, transform=transform, download=True)
```

```
train_loader = torch.utils.data.DataLoader(train_dataset,␣
↪batch_size=batch_size, shuffle=True)

test_dataset = torchvision.datasets.MNIST(
    root="../data/", train=False, transform=transform, download=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size,␣
↪shuffle=True)
```

[4]:

```
# use gpu if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
input_shape = [1, 28, 28]
enc_dim = 400
latent_dim = 2
num_epochs = 50
logDir = "models_and_stats/"
```

0.2 Load models

[5]:

```
model_names = ["MLP_AE_l2", "MLP_VAE_dist_l2_wkl_10_wr_1",␣
↪"MLP_VAE_dist_l2_wkl_10_wr_0", "MLP_CVAE_dist_l2_wkl_10_wr_1"]
short_names = ["recon only (AE)", "recon + kl", "kl only", "CVAE"]
model1 = MLP_AE(input_shape=input_shape, latent_dim=latent_dim)
model2 = MLP_VAE(input_shape=input_shape, enc_dim=enc_dim,␣
↪latent_dim=latent_dim)
model3 = MLP_VAE(input_shape=input_shape, enc_dim=enc_dim,␣
↪latent_dim=latent_dim)
model4 = MLP_CVAE(input_shape=input_shape, enc_dim=enc_dim,␣
↪latent_dim=latent_dim)
models = [model1, model2, model3, model4]
results_dicts = []
for i in range(len(models)):
    print("loading model for {}".format(model_names[i]))
    model = models[i]
    model_path = logDir + model_names[i] + ".pt"
    model.load_state_dict(torch.load(model_path))
    model.to(device)
    model.eval()
    dict_name = model_names[i] + '.pkl'
    results_dicts.append(pickle.load(open(logDir + dict_name, 'rb')))
```

```
loading model for MLP_AE_l2
loading model for MLP_VAE_dist_l2_wkl_10_wr_1
loading model for MLP_VAE_dist_l2_wkl_10_wr_0
loading model for MLP_CVAE_dist_l2_wkl_10_wr_1
```

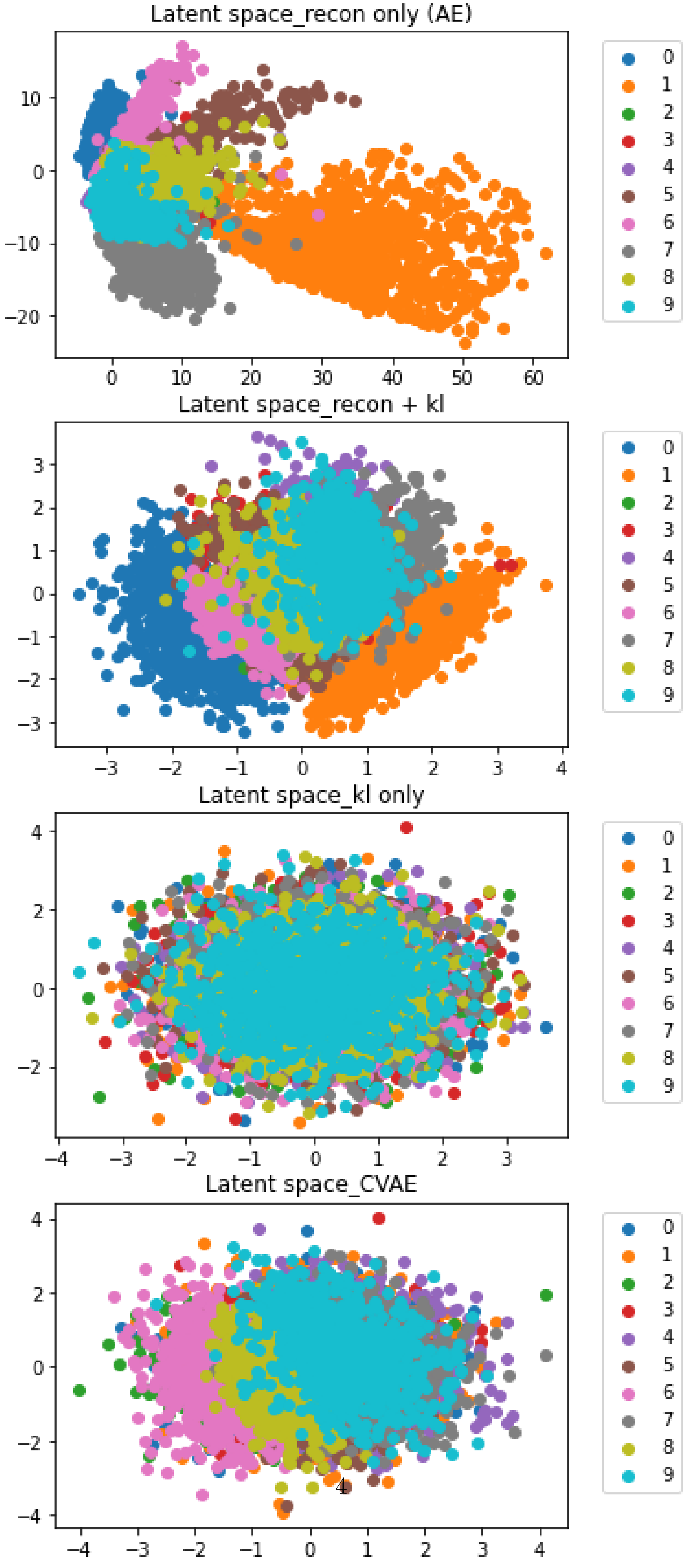
0.2.1 1. compare latent space

[6]:

```
# plot the whole test latent space
all_test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=10000,␣
 ↪shuffle=True)
all_test_imgs, all_test_labels = next(iter(all_test_loader))
all_test_imgs, all_test_labels = torch.tensor(all_test_imgs).float().
 ↪to(device), torch.tensor(all_test_labels).to(device)
```

[7]:

```
all_test_latents_list = []
fig, axes = plt.subplots(nrows=len(models), ncols=1, figsize=(5,15))
for i in range(len(models)):
    model = models[i]
    if i == 0: # AE
        all_test_latents, all_test_reconstructions = model(all_test_imgs)
    elif i == 3: # CVAE
        all_test_latents, all_test_reconstructions, all_test_latent_means,␣
 ↪all_test_latent_logvars = model(all_test_imgs, all_test_labels)
    else: # VAE
        all_test_latents, all_test_reconstructions, all_test_latent_means,␣
 ↪all_test_latent_logvars = model(all_test_imgs)
    plot_latent(all_test_labels, all_test_latents, dtype="tensor",␣
 ↪suptitle_app="_{}".format(short_names[i]), ax=axes[i], add_legend=True)

    all_test_latents_list.append(all_test_latents)
```

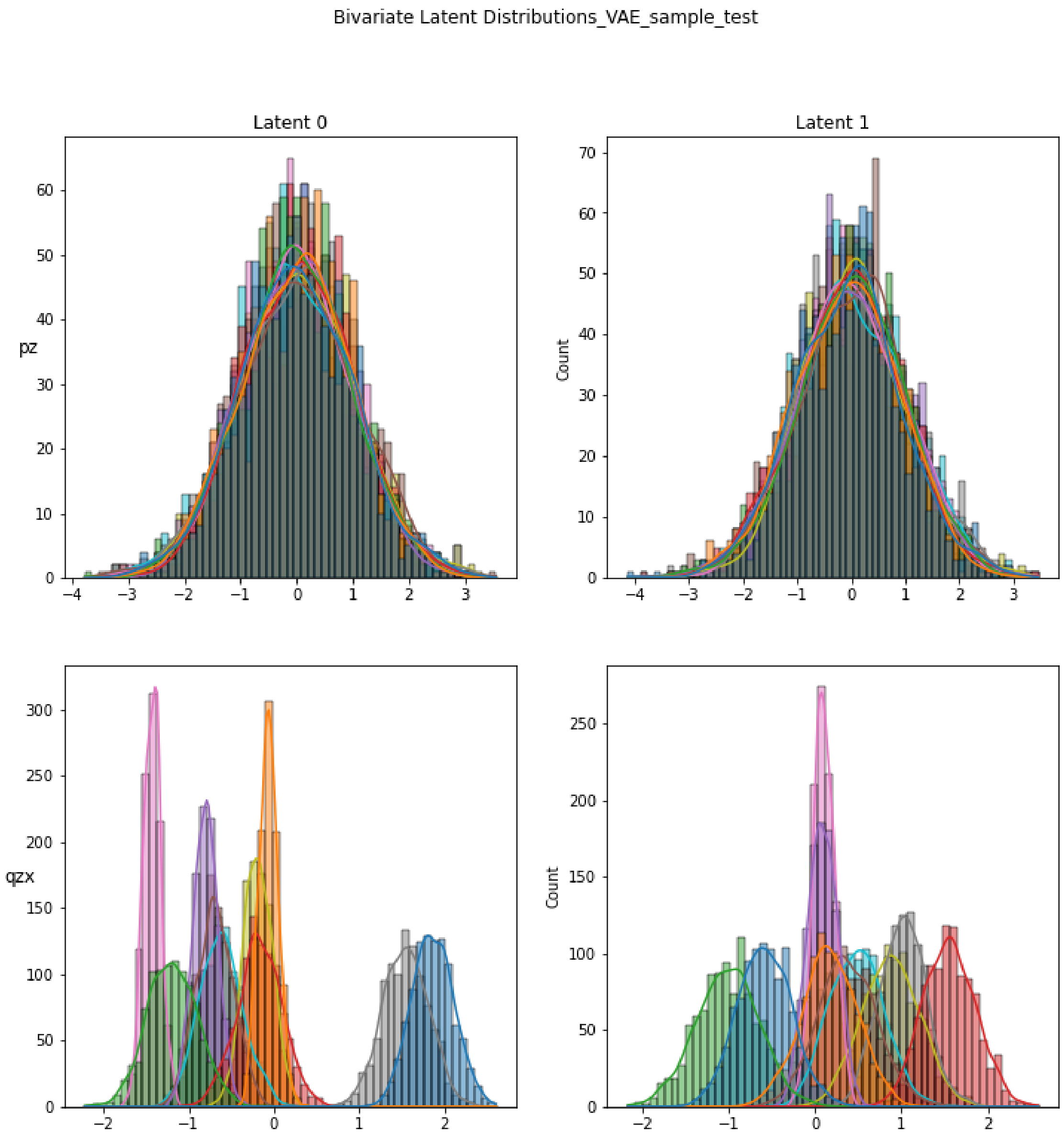

Latent space_recon only (AE)
10
0
−10
−20
0
10
20
30
40
50
60
0
1
2
3
4
5
6
7
8
9
Latent space_recon + kl
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3
4
0
1
2
3
4
5
6
7
8
9
Latent space_kl only
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
0
1
2
3
4
5
6
7
8
9
Latent space_CVAE
4
2
0
−2
−4
−4
−3
−2
−1
0
1
2
3
4
0
1
2
3
4
5
6
7
8
9

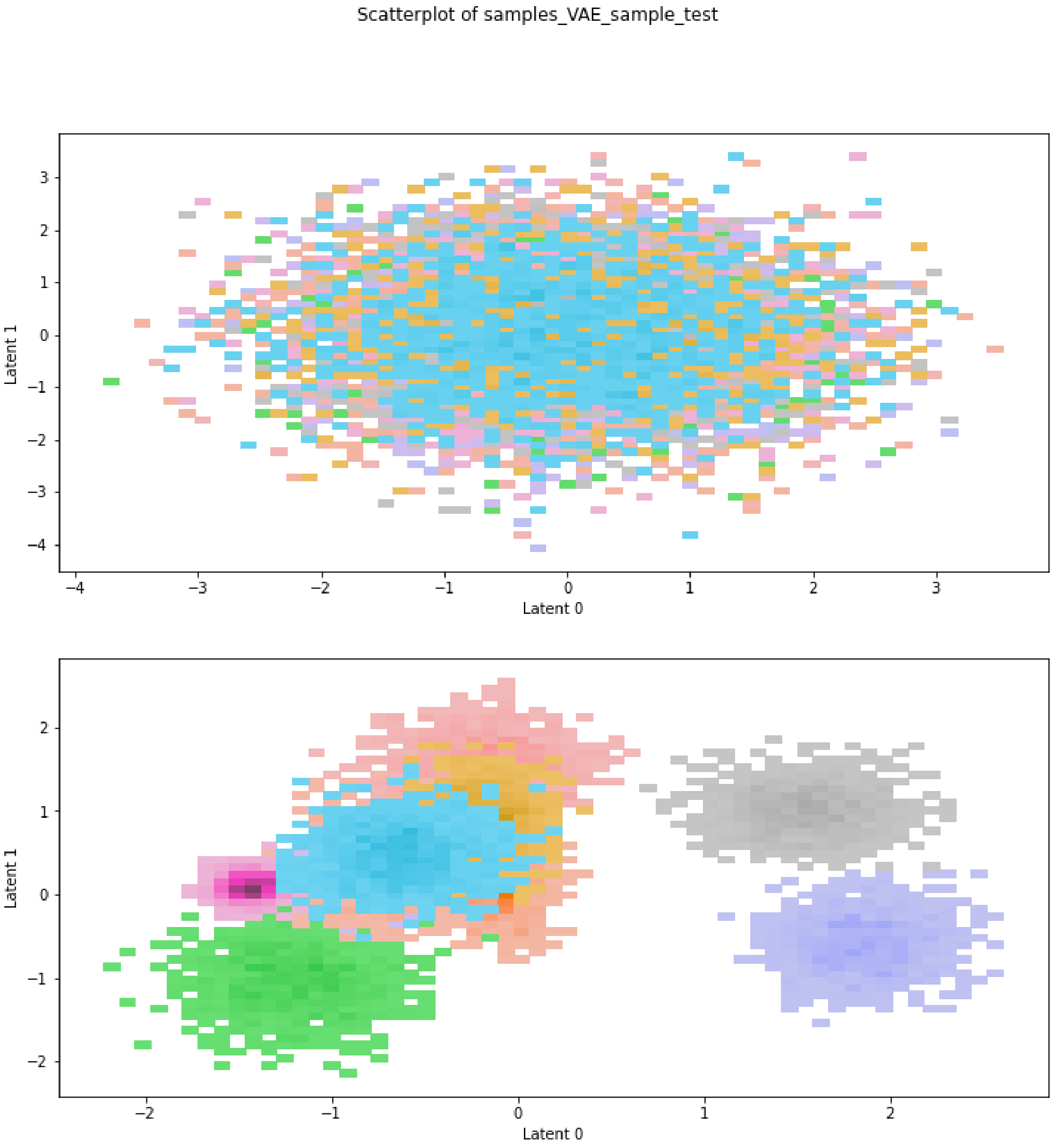
0.2.2 2. plot VAE latent distribution

[8]:

```
num_sample = 10
sample_test_imgs, sample_test_labels = all_test_imgs[:num_sample,...],␣
 ↪all_test_labels[:num_sample,...]
VAE = models[1]
sample_test_latents, sample_test_reconstructions, sample_test_latent_mean,␣
 ↪sample_test_latent_logvar = VAE(sample_test_imgs)
plot_p_q(sample_test_latent_mean, sample_test_latent_logvar, N_samples=1000,␣
 ↪suptitle_app="_VAE_sample_test")
```

```
Plot bivariate latent distributions
pz batch_shape torch.Size([10, 2]), event_shape torch.Size([])
qzx batch_shape torch.Size([10, 2]), event_shape torch.Size([])
check p, q shape, pz (1000, 10, 2), qzx (1000, 10, 2)
```


Bivariate Latent Distributions_VAE_sample_test
Latent 0
Latent 1
pz
qzx
Count
Count
0
10
20
30
40
50
60
70
−4
−3
−2
−1
0
1
2
3
0
50
100
150
200
250
300
−2
−1
0
1
2


Scatterplot of samples_VAE_sample_test

0.2.3 3. compare sampling around

Assume gaussian distribution for each latent variable, AE takes latent as mean, std=1 VAE takes latent mean & var

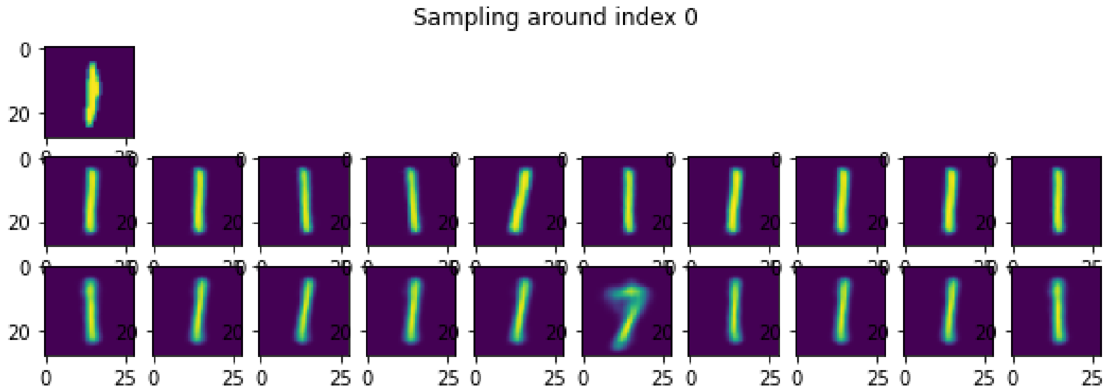
[9]:
```
num_sample = 10 # number of images
sample_test_imgs, sample_test_labels = all_test_imgs[:num_sample,...],␣
 ↪all_test_labels[:num_sample,...]
AE = models[0]
```

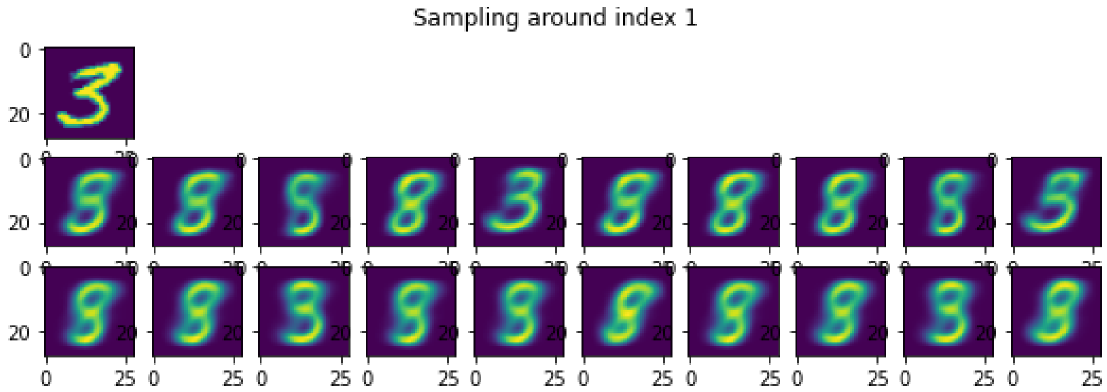
```
VAE = models[1]
N_samples = 10 # number of samples drawn from latent space
sample_test_latents_AE, sample_test_reconstruction_AE = AE(sample_test_imgs)
_, sample_test_reconstruction_VAE, sample_test_latent_mean_VAE,␣
 ↪sample_test_latent_logvar_VAE = VAE(sample_test_imgs)
```

[10]:

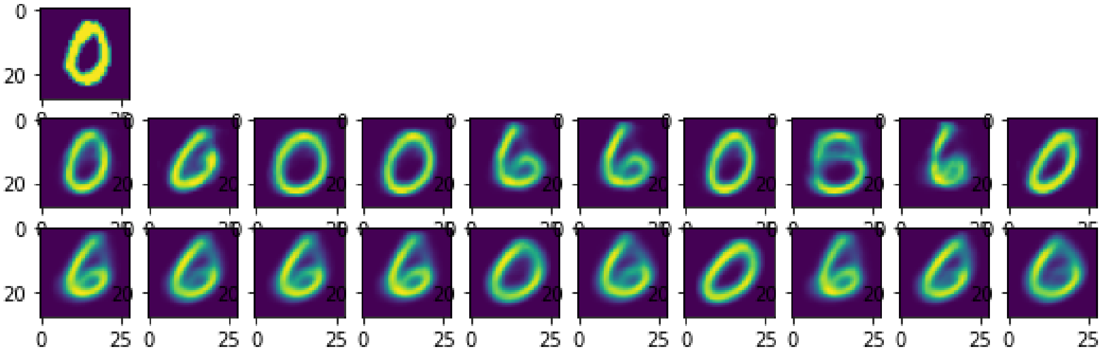
```
rows = ["original image", "AE recon", "VAE recon"]
n_rows = 3
for index in np.arange(num_sample):
    latent_AE = sample_test_latents_AE[index]
    sample_z_AE = sample_latent_embedding(latent_AE, sd=1,␣
 ↪N_samples=N_samples-1)
    recon_sample_z_AE = AE.decoder(sample_z_AE)

    latent_VAE_mean = sample_test_latent_mean_VAE[index]
    latent_VAE_logvar = sample_test_latent_logvar_VAE[index]
    latent_VAE_std = torch.exp(0.5*latent_VAE_logvar)
    sample_z_VAE = sample_latent_embedding(latent_VAE_mean, sd=latent_VAE_std,␣
 ↪N_samples=N_samples-1)
    recon_sample_z_VAE = VAE.decoder(sample_z_VAE)

#     figure, axes = plt.subplots(nrows=3, ncols=N_samples,␣
 ↪figsize=(N_samples,3))
    figure = plt.figure(figsize=(N_samples,3))
    figure.suptitle("Sampling around index {}".format(index))
    img = sample_test_imgs[index].cpu().detach().numpy()
    reconstruction_AE = sample_test_reconstruction_AE[index].cpu().detach().
 ↪numpy()
    reconstruction_VAE = sample_test_reconstruction_VAE[index].cpu().detach().
 ↪numpy()

    plt.subplot(3, N_samples, 1)
    plt.imshow(img[0])

    plt.subplot(3, N_samples, N_samples+1)
    plt.imshow(reconstruction_AE[0])
    for i, recon in enumerate(recon_sample_z_AE.cpu().detach().numpy()):
        plt.subplot(3, N_samples, N_samples+i+2)
        plt.imshow(recon[0])

    plt.subplot(3, N_samples, 2*N_samples+1)
    plt.imshow(reconstruction_VAE[0])
    for i, recon in enumerate(recon_sample_z_VAE.cpu().detach().numpy()):
        plt.subplot(3, N_samples, 2*N_samples+i+2)
        plt.imshow(recon[0])

#     for ax, row in zip(axes[:,0], rows):
```

```
#           ax.set_ylabel(row, rotation=0, size='large')
#       plt.show()

#       for i in range(n_rows):
#           axes[i][0].text(x = -0.8, y = 5, s = rows[i], rotation = 90, va = "center")
#       plt.show()
```

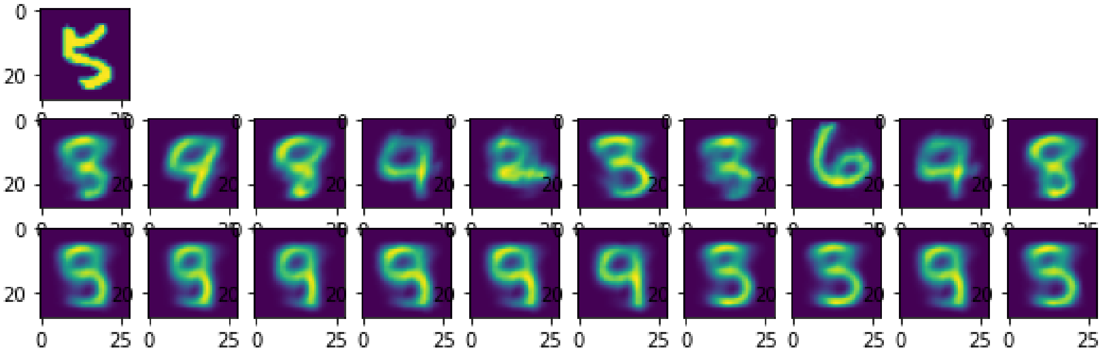




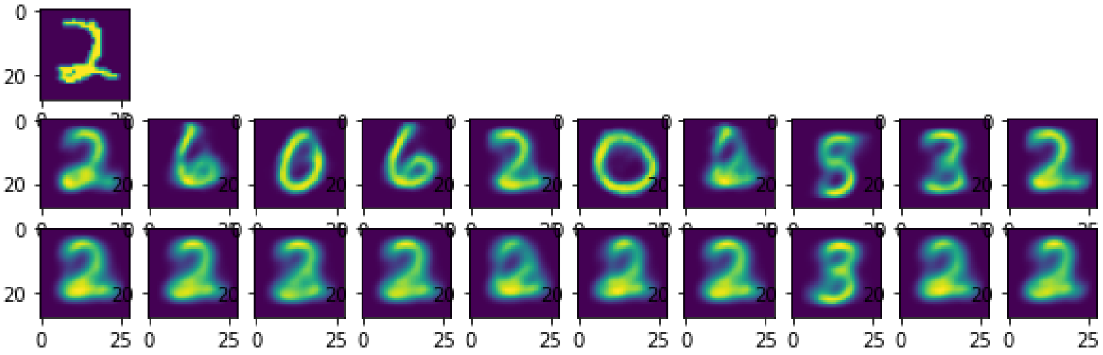
Sampling around index 2

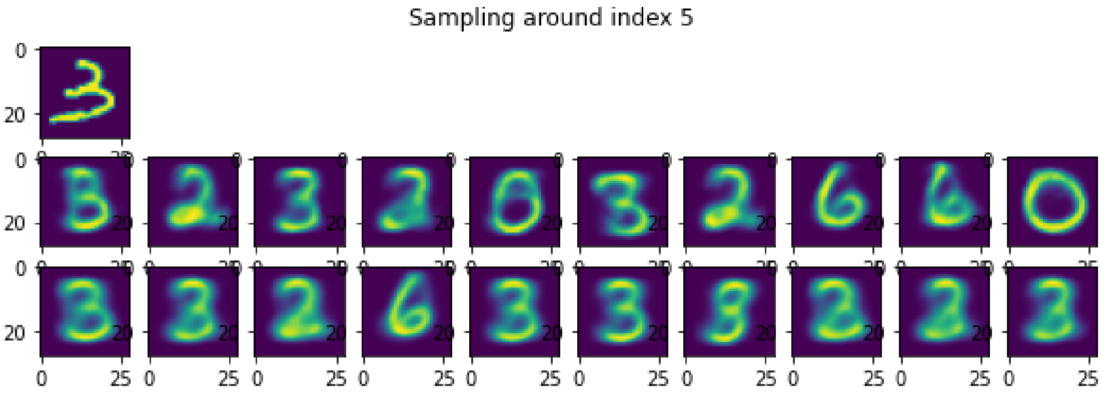


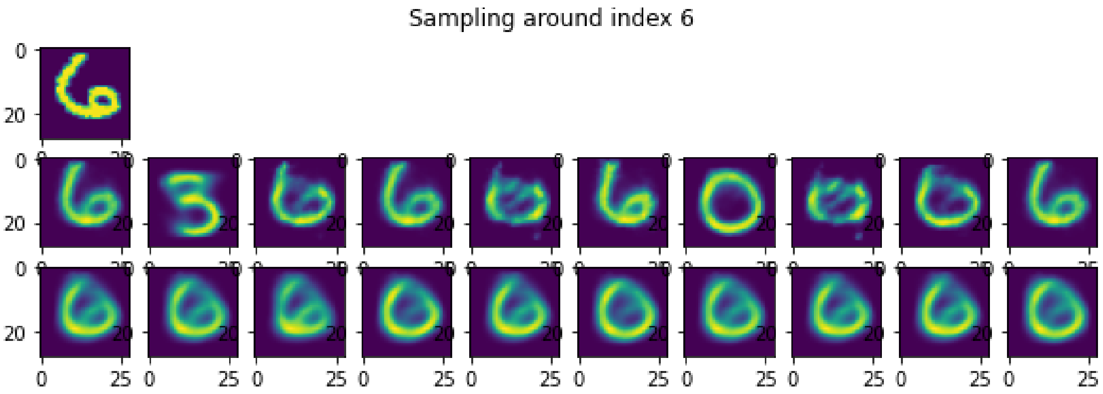
Sampling around index 3

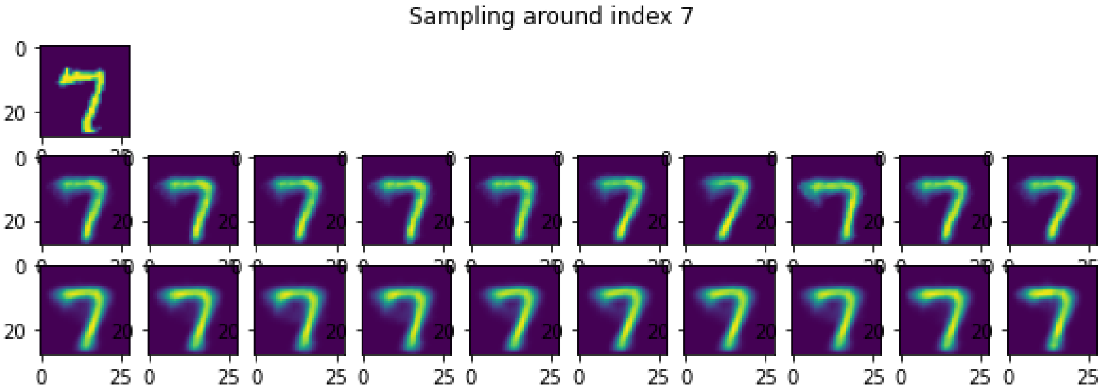


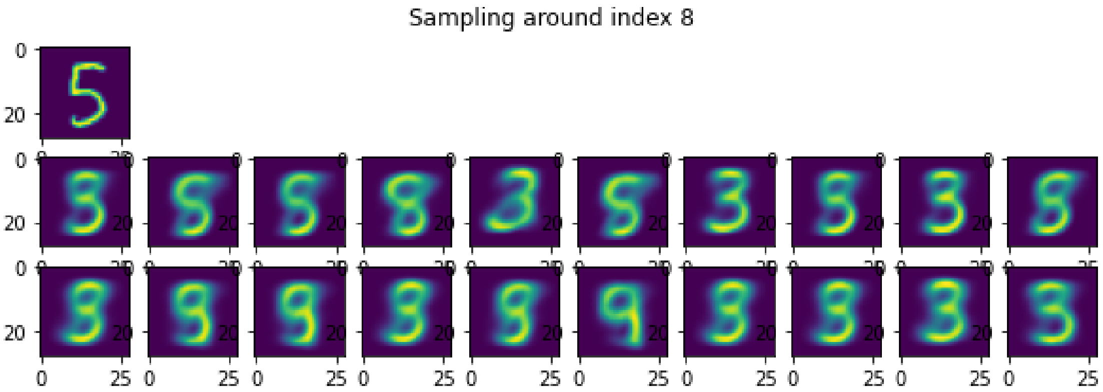
Sampling around index 4

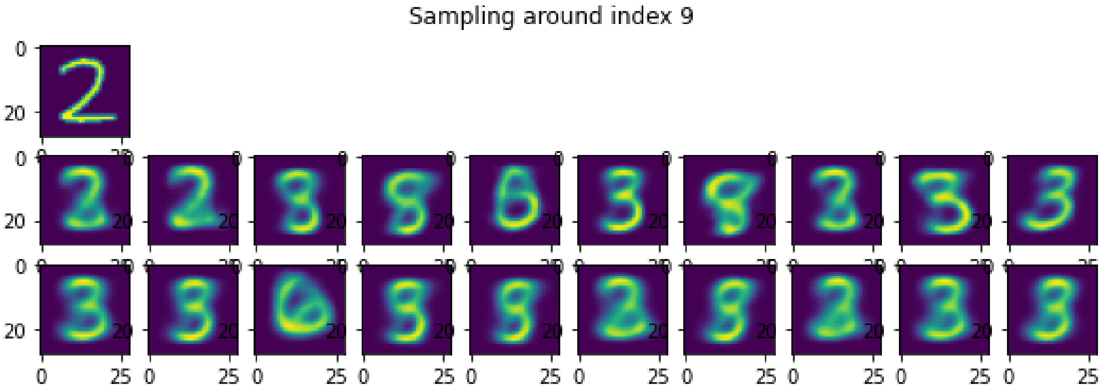



Sampling around index 5
0
20
0
25


Sampling around index 6
0
20
0
25


Sampling around index 7
0
20
0
25

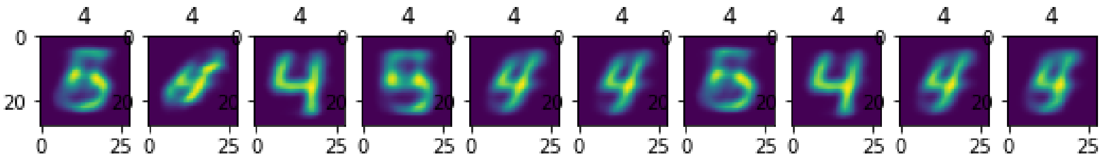




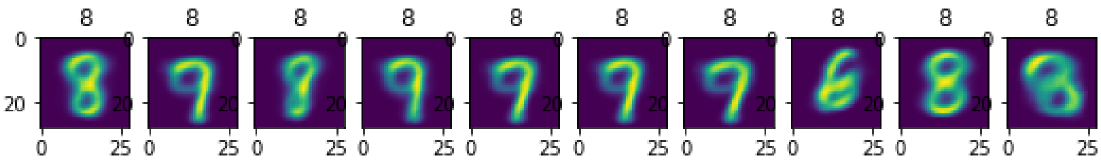
0.2.4 4. plot CVAE reconstruction, given labels

[11]:
```
CVAE = models[3]
```

[12]:
```
y = 4
generate_data_cond_y(CVAE, y, num_samples=10, latent_dim=2, device=device)
```

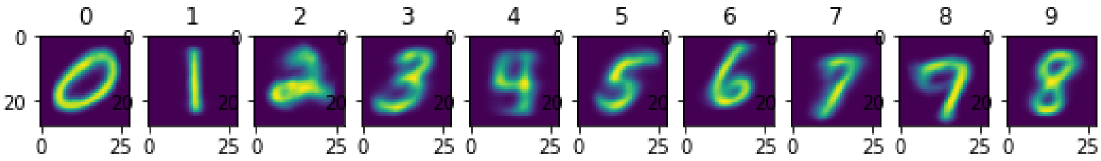


[13]:
```
y = 8
generate_data_cond_y(model, y, num_samples=10, latent_dim=2, device=device)
```



[14]:

```
y = np.arange(10)
generate_data_cond_y(model, y, latent_dim=2, device=device)
```



[ ]:

```
```