Idee 1: The lazy mans way

Trainiere 10 VAE, jeweils mit den Samples einer Klasse von MNIST. Wir haben dann 10 VAE, jeder spezialisiert auf die Generierung einer Zahl. Immer wenn wir eine Zahl generieren müssen, benutzen wir dafür den jeweiligen spezialisierten VAE.

Idee 2: Wie auf dem Zettel vorgeschlagen mithilfe von Conditional Variational Autencodern (CVAE) ¶

In [1]:
```
import torch
import torchvision
import torchvision.transforms as transforms
from torch import nn
from tqdm import tqdm
import matplotlib.pyplot as plt
import numpy as np
import multiprocessing
```

In [2]:
```
if torch.cuda.is_available():
    device = "cuda"
    print("Training on gpu")
else:
    device = "cpu"
    print("Training on cpu")
```

```
Training on gpu
```

In [3]:
```
def to_onehot(digits, num_classes, device):
    """ [[3]] => [[0, 0, 1]]
    """
    labels_onehot = torch.zeros(digits.shape[0], num_classes).to(device)
    labels_onehot.scatter_(1, digits.view(-1, 1), 1)
    return labels_onehot



class CCVAE(nn.Module):
    """ Conditional convolutional variational autoencoder.
    """
    def __init__(self, input_channels, lat_dim, num_classes, device):
        super().__init__()
        self.conv1_ds = nn.Conv2d(input_channels + num_classes, 16, kern
        self.conv2_ds = nn.Conv2d(16, 32, kernel_size=(3, 3), stride=(2,
        self.conv3_ds = nn.Conv2d(32, 64, kernel_size=(3, 3), stride=(2,
        self.dense_enc_mean = nn.Linear(4 * 4 * 64, lat_dim)
        self.dense_enc_std = nn.Linear(4 * 4 *64, lat_dim)
        self.dense_dec = nn.Linear(lat_dim + num_classes, 4 * 4 * 64)
        self.deconv_3 = nn.ConvTranspose2d(64, 32, kernel_size=(3, 3), s
        self.deconv_2 = nn.ConvTranspose2d(32, 16, kernel_size=(3, 3), s
        self.deconv_1 = nn.ConvTranspose2d(16, 1, kernel_size=(3, 3), st
        self.lat_dim = lat_dim
        self.num_classes = num_classes
        self.device = device

    def encode(self, x, y):
        """ The next 5 lines of code were taken from https://github.com/
        since it was the only reference on how to use a conditional vari
        What we do is add num_classes channels to the input, where we se
        to have only ones and the rest of the channels to have only zero
        """
        y_onehot = to_onehot(y, self.num_classes, self.device)
        y_onehot = y_onehot.view(-1, self.num_classes, 1, 1)
        ones = torch.ones(x.shape[0],
                          self.num_classes,
                          x.shape[2],
                          x.shape[3],
                          dtype=x.dtype).to(self.device)
        ones = ones * y_onehot
        x = torch.cat((x, ones), dim=1)

        x = self.conv1_ds(x)
        x = nn.functional.relu(x)
        x = self.conv2_ds(x)
        x = nn.functional.relu(x)
        x = self.conv3_ds(x)
        x = nn.functional.relu(x)
        x = torch.flatten(x, 1)
        mean, std = self.dense_enc_mean(x), self.dense_enc_std(x)
        return mean, std

    def decode(self, x, y):
        """ Just append the one hot vector as features
        """
```

```
        y_onehot = to_onehot(y, self.num_classes, self.device)
        x = torch.cat((x, y_onehot), dim=1)

        x = self.dense_dec(x)
        x = nn.functional.relu(x)
        x = torch.reshape(x, (x.shape[0], 64, 4, 4))
        x = self.deconv_3(x)
        x = nn.functional.relu(x)
        x = self.deconv_2(x)
        x = nn.functional.relu(x)
        x = self.deconv_1(x)
        """ Trick to make sure all outputs are in range (0, 1)
        """
        x = torch.sigmoid(x)
        return x

    def forward(self, x, y):
        mean, std = self.encode(x, y)
        latent = self.reparameterize(mean, std)
        out = self.decode(latent, y)
        return out, mean, std

    def reparameterize(self, mean, std):
        eps = torch.randn_like(mean).to(self.device)
        return eps * std + mean

    def generate(self, y):
        with torch.no_grad():
            eps = torch.randn((y.shape[0], self.lat_dim)).to(self.device
            return self.decode(eps, y)

def kl_divergence(mean, std):
    variance = std.pow(2)
    inner = mean.pow(2) + variance - 1 - torch.log(variance)
    return (1/2) * torch.sum(inner)

trainset = torchvision.datasets.MNIST(root='./data', train=True,
                                        download=True, transform=transfo

testset = torchvision.datasets.MNIST(root='./data', train=False,
                                       download=True, transform=transfor

dataset = torch.utils.data.ConcatDataset((trainset, testset))
ds_loader = torch.utils.data.DataLoader(dataset, batch_size=128,
                                         shuffle=True, num_workers=multi
```

In [4]:

```
generator = CCVAE(1, 50, num_classes=10, device=device).to(device)
```

In [5]:
```
num_epochs = 60
bce_loss = torch.nn.BCELoss(reduction='sum')
optimizer = torch.optim.Adam(generator.parameters(), lr=0.0005)

rec_losses = []
kl_losses = []
generator.train()
for epoch in range(1, num_epochs + 1):
    running_rec_loss = 0
    running_kl_loss = 0
    iterations = 0
    for x, y in ds_loader:
        x, y = x.to(device), y.to(device)
        optimizer.zero_grad()
        reconstruction, mean, std = generator(x, y)
        reconstruction = reconstruction.view(x.shape[0], -1)
        x = x.view(x.shape[0], -1)
        reconstruction_loss = bce_loss(reconstruction, x)
        kl_loss = kl_divergence(mean, std)
        loss = reconstruction_loss + kl_loss
        loss.backward()
        optimizer.step()
        running_rec_loss += loss.item()
        running_kl_loss += kl_loss.item()
        iterations += 1

    rec_loss = running_rec_loss / iterations
    kl_loss = running_kl_loss / iterations
    rec_losses.append(rec_loss)
    kl_losses.append(kl_loss)
    print(f"Epoch {epoch}/{num_epochs} ==> rec_loss: {rec_loss}, kl_loss
```

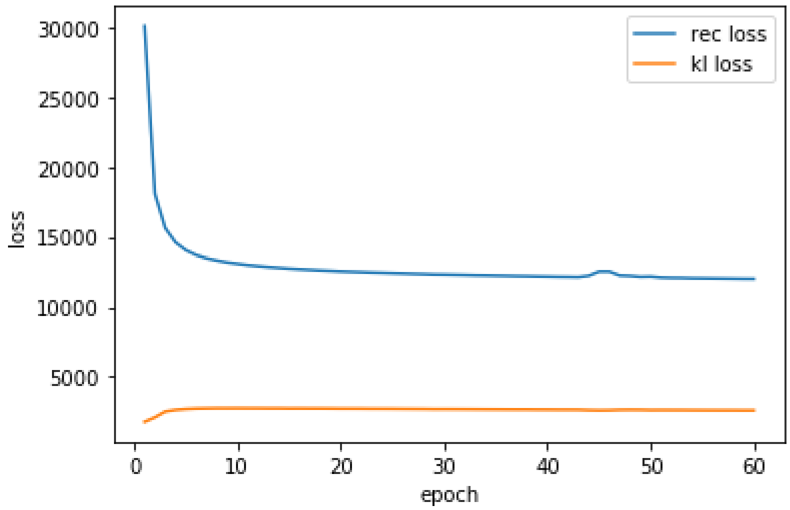
```
Epoch 1/60 ==> rec_loss: 30081.75284934872, kl_loss: 1787.62727024001
65, total: 31869.380119588735
Epoch 2/60 ==> rec_loss: 18083.442659534965, kl_loss: 2107.2823285481
177, total: 20190.724988083082
Epoch 3/60 ==> rec_loss: 15634.292597406307, kl_loss: 2523.2986763739
72, total: 18157.59127378028
Epoch 4/60 ==> rec_loss: 14612.496759669219, kl_loss: 2639.2583945098
263, total: 17251.755154179045
Epoch 5/60 ==> rec_loss: 14054.153850548446, kl_loss: 2700.7078060728
977, total: 16754.861656621342
Epoch 6/60 ==> rec_loss: 13707.16146309415, kl_loss: 2735.93582627542
26, total: 16443.097289369573
Epoch 7/60 ==> rec_loss: 13471.554119772623, kl_loss: 2749.1126430030
28, total: 16220.66676277565
Epoch 8/60 ==> rec_loss: 13313.576966336266, kl_loss: 2760.7806059507
825, total: 16074.357572287048
Epoch 9/60 ==> rec_loss: 13178.048190770682, kl_loss: 2759.7957440085
124, total: 15937.843934779194
Epoch 10/60 ==> rec_loss: 13083.234930230234, kl_loss: 2761.731496640
0536, total: 15844.966426870287
Epoch 11/60 ==> rec_loss: 12986.529670004, kl_loss: 2758.995866123457
3, total: 15745.525536127458
Epoch 12/60 ==> rec_loss: 12915.440485031993, kl_loss: 2758.072591889
711, total: 15673.513076921705
Epoch 13/60 ==> rec_loss: 12847.002588694013, kl_loss: 2752.702879966
```

```
722, total: 15599.705468660735
Epoch 14/60 ==> rec_loss: 12791.610883583753, kl_loss: 2753.224501363
974, total: 15544.835384947728
Epoch 15/60 ==> rec_loss: 12736.2965590008, kl_loss: 2744.52450332781
06, total: 15480.82106232861
Epoch 16/60 ==> rec_loss: 12691.820330353063, kl_loss: 2746.051061989
4026, total: 15437.871392342466
Epoch 17/60 ==> rec_loss: 12652.776333266682, kl_loss: 2743.152761065
328, total: 15395.92909433201
Epoch 18/60 ==> rec_loss: 12612.47732661106, kl_loss: 2742.0506928773
425, total: 15354.528019488404
Epoch 19/60 ==> rec_loss: 12579.032767510284, kl_loss: 2738.046396984
261, total: 15317.079164494544
Epoch 20/60 ==> rec_loss: 12541.719465907792, kl_loss: 2731.967893053
0163, total: 15273.687358960808
Epoch 21/60 ==> rec_loss: 12516.00598613174, kl_loss: 2730.8294019402
706, total: 15246.835388072011
Epoch 22/60 ==> rec_loss: 12491.793825696983, kl_loss: 2728.370319819
7554, total: 15220.164145516737
Epoch 23/60 ==> rec_loss: 12463.258401651052, kl_loss: 2721.903667554
559, total: 15185.162069205611
Epoch 24/60 ==> rec_loss: 12443.533354876028, kl_loss: 2719.774295785
963, total: 15163.307650661991
Epoch 25/60 ==> rec_loss: 12419.077773294675, kl_loss: 2717.984419632
6553, total: 15137.062192927331
Epoch 26/60 ==> rec_loss: 12397.023730290219, kl_loss: 2711.560808868
687, total: 15108.584539158906
Epoch 27/60 ==> rec_loss: 12372.687746372258, kl_loss: 2706.988088436
9286, total: 15079.675834809186
Epoch 28/60 ==> rec_loss: 12354.281776665333, kl_loss: 2703.376662566
4134, total: 15057.658439231747
Epoch 29/60 ==> rec_loss: 12327.314722706238, kl_loss: 2693.435268367
2305, total: 15020.74999107347
Epoch 30/60 ==> rec_loss: 12319.554521466522, kl_loss: 2694.472770509
598, total: 15014.02729197612
Epoch 31/60 ==> rec_loss: 12304.776809943442, kl_loss: 2691.912728429
93, total: 14996.689538373372
Epoch 32/60 ==> rec_loss: 12290.099298731719, kl_loss: 2687.871318252
2565, total: 14977.970616983976
Epoch 33/60 ==> rec_loss: 12270.318127285193, kl_loss: 2684.365646334
409, total: 14954.683773619601
Epoch 34/60 ==> rec_loss: 12261.129568598606, kl_loss: 2679.433068869
9724, total: 14940.562637468578
Epoch 35/60 ==> rec_loss: 12244.100778750571, kl_loss: 2676.263898608
8896, total: 14920.364677359461
Epoch 36/60 ==> rec_loss: 12231.26917775937, kl_loss: 2672.7466922739
09, total: 14904.01587003328
Epoch 37/60 ==> rec_loss: 12215.929760697554, kl_loss: 2669.035791372
686, total: 14884.96555207024
Epoch 38/60 ==> rec_loss: 12206.310580795818, kl_loss: 2668.668823465
3507, total: 14874.979404261168
Epoch 39/60 ==> rec_loss: 12188.761620558158, kl_loss: 2661.161454167
619, total: 14849.923074725777
Epoch 40/60 ==> rec_loss: 12178.716180944355, kl_loss: 2658.634580399
48, total: 14837.350761343834
Epoch 41/60 ==> rec_loss: 12163.435189813757, kl_loss: 2652.961678402
0795, total: 14816.396868215837
```

```
Epoch 42/60 ==> rec_loss: 12156.427221992117, kl_loss: 2651.672971178
0163, total: 14808.100193170132
Epoch 43/60 ==> rec_loss: 12142.871454381855, kl_loss: 2649.312137582
838, total: 14792.183591964693
Epoch 44/60 ==> rec_loss: 12237.563480133113, kl_loss: 2624.085980793
676, total: 14861.649460926788
Epoch 45/60 ==> rec_loss: 12536.912998457496, kl_loss: 2611.138259022
9377, total: 15148.051257480434
Epoch 46/60 ==> rec_loss: 12537.824265167961, kl_loss: 2618.241697433
4437, total: 15156.065962601406
Epoch 47/60 ==> rec_loss: 12256.692520281078, kl_loss: 2643.429957973
8918, total: 14900.122478254969
Epoch 48/60 ==> rec_loss: 12228.50857125514, kl_loss: 2648.7922385597
576, total: 14877.300809814898
Epoch 49/60 ==> rec_loss: 12162.974105918647, kl_loss: 2644.867536973
6916, total: 14807.84164289234
Epoch 50/60 ==> rec_loss: 12179.957307972463, kl_loss: 2628.688343557
1867, total: 14808.64565152965
Epoch 51/60 ==> rec_loss: 12107.6432958181, kl_loss: 2631.42242130370
2, total: 14739.0657171218
Epoch 52/60 ==> rec_loss: 12087.409026151165, kl_loss: 2629.584727955
039, total: 14716.993754106203
Epoch 53/60 ==> rec_loss: 12081.512741730461, kl_loss: 2628.054874064
4995, total: 14709.56761579496
Epoch 54/60 ==> rec_loss: 12060.763768281535, kl_loss: 2622.791496318
6986, total: 14683.555264600232
Epoch 55/60 ==> rec_loss: 12054.14389032507, kl_loss: 2619.5987684957
72, total: 14673.742658820842
Epoch 56/60 ==> rec_loss: 12043.722136725892, kl_loss: 2616.334421328
6964, total: 14660.056558054588
Epoch 57/60 ==> rec_loss: 12036.184247172076, kl_loss: 2614.146350030
7073, total: 14650.330597202783
Epoch 58/60 ==> rec_loss: 12026.976151879571, kl_loss: 2613.773999871
458, total: 14640.750151751028
Epoch 59/60 ==> rec_loss: 12017.260172674818, kl_loss: 2609.001581781
3073, total: 14626.261754456125
Epoch 60/60 ==> rec_loss: 12013.707656107175, kl_loss: 2609.105831167
162, total: 14622.813487274338
```

In [6]:
```
plt.plot(list(range(1, len(rec_losses)  + 1)), rec_losses, label="rec lo
plt.plot(list(range(1, len(kl_losses)  + 1)), kl_losses, label="kl loss"
plt.xlabel("epoch")
plt.ylabel("loss")
plt.legend()
plt.plot()
```

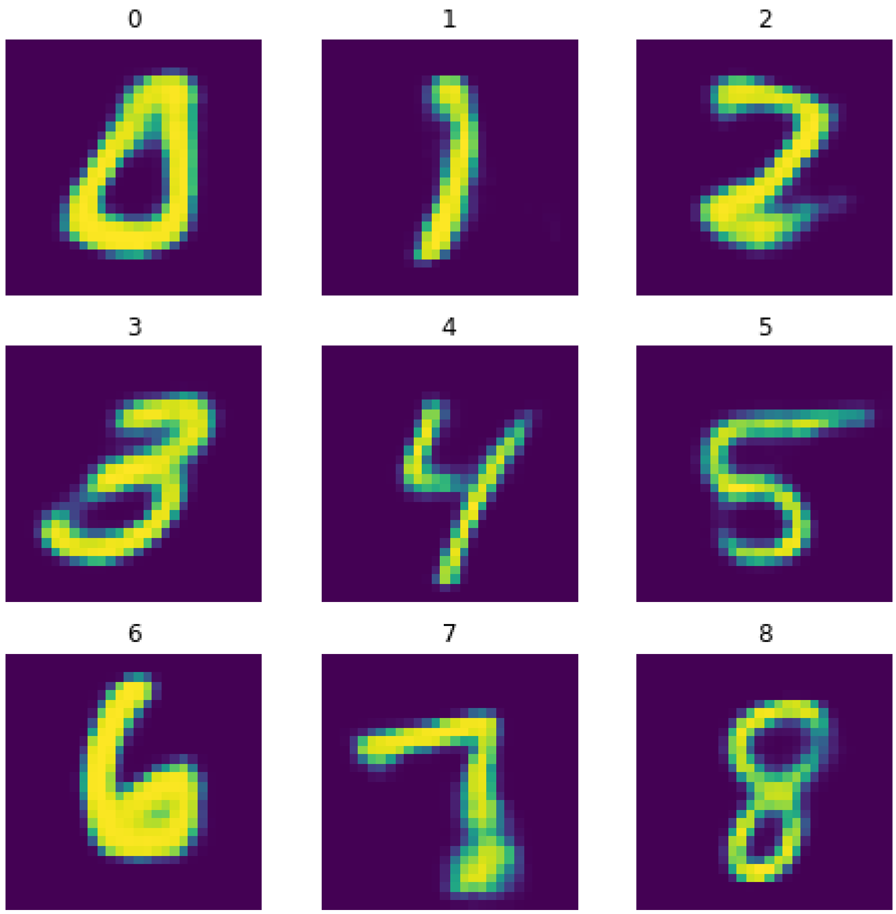
Out[6]: []



In [7]:
```
generator.eval()
classes = torch.cuda.LongTensor(list(range(10)))
samples = generator.generate(classes).cpu().numpy()

fig, ax = plt.subplots(nrows=3, ncols=3, figsize=(8, 8))

for col in range(ax.shape[1]):
    for row in range(ax.shape[0]):
        img = samples[col + row * 3]
        ax[row][col].imshow(img.reshape((28, 28)))
        ax[row][col].set_title(col + row * 3)
        ax[row][col].axis('off')
```



In [8]:
```
def get_digit(number, n_th_digit):
    return number // 10 ** n_th_digit % 10

digits = 20
pi = np.pi

digits = [int(get_digit(pi, n_th_digit)) for n_th_digit in range(0, -20,
classes = torch.cuda.LongTensor(digits)
```

In [9]:
```
for experiment in range(1, 6):
    samples = generator.generate(classes).cpu().numpy()
    samples = samples.reshape((-1, 28, 28))
    samples_stacked = np.hstack(tuple(samples))
    plt.figure(figsize=(15, 15))
    plt.imshow(samples_stacked)
    plt.title(f"experiment {experiment}")
    plt.axis('off')
    plt.show()
```

experiment 1

experiment 2

experiment 3

experiment 4

experiment 5