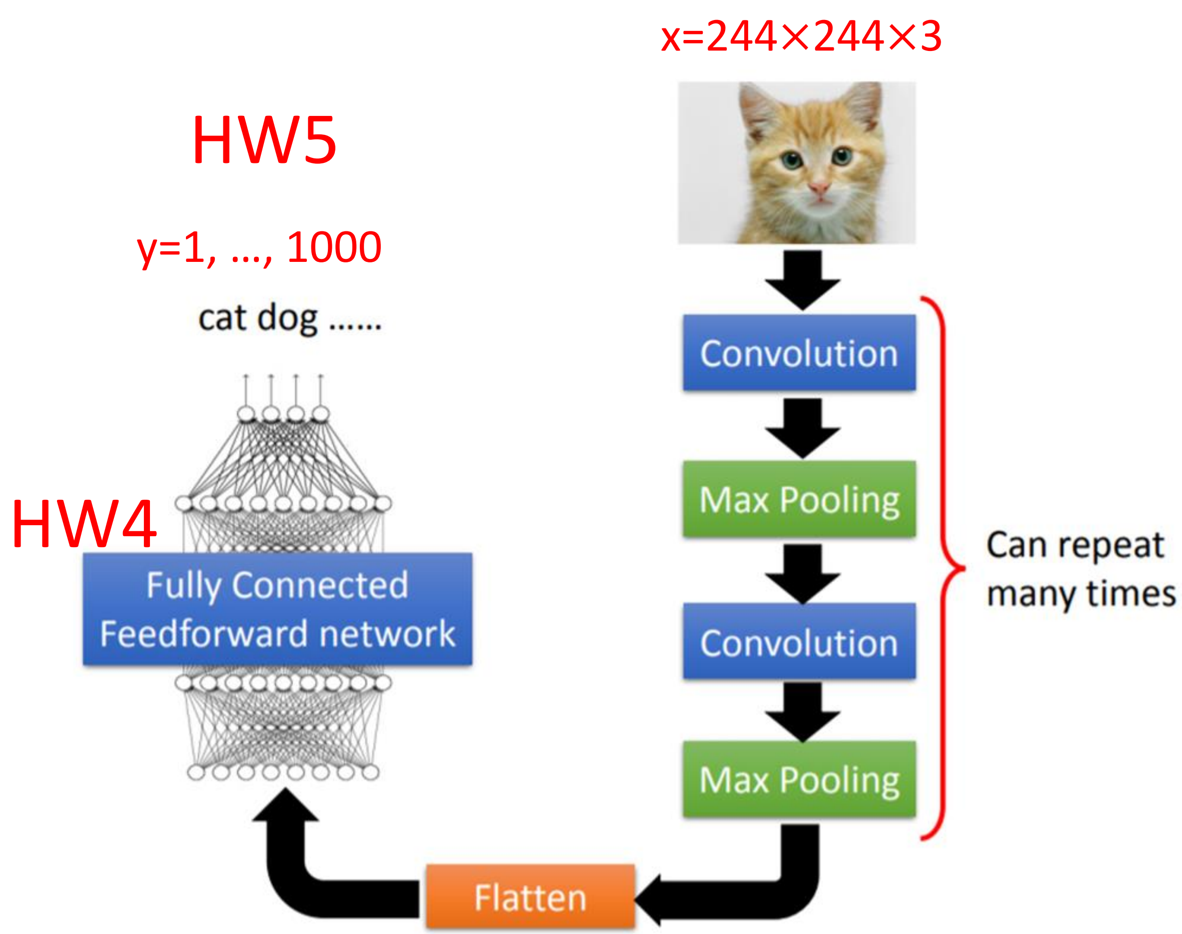
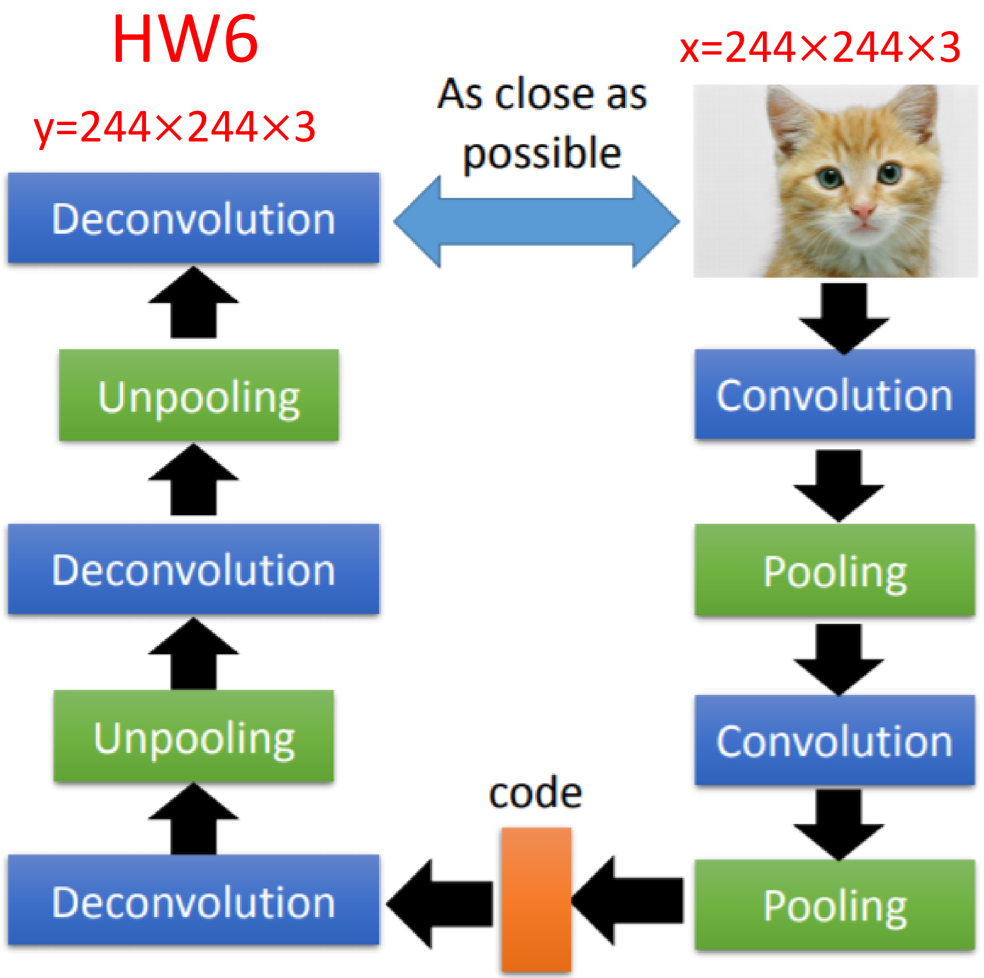
Auto-encoder

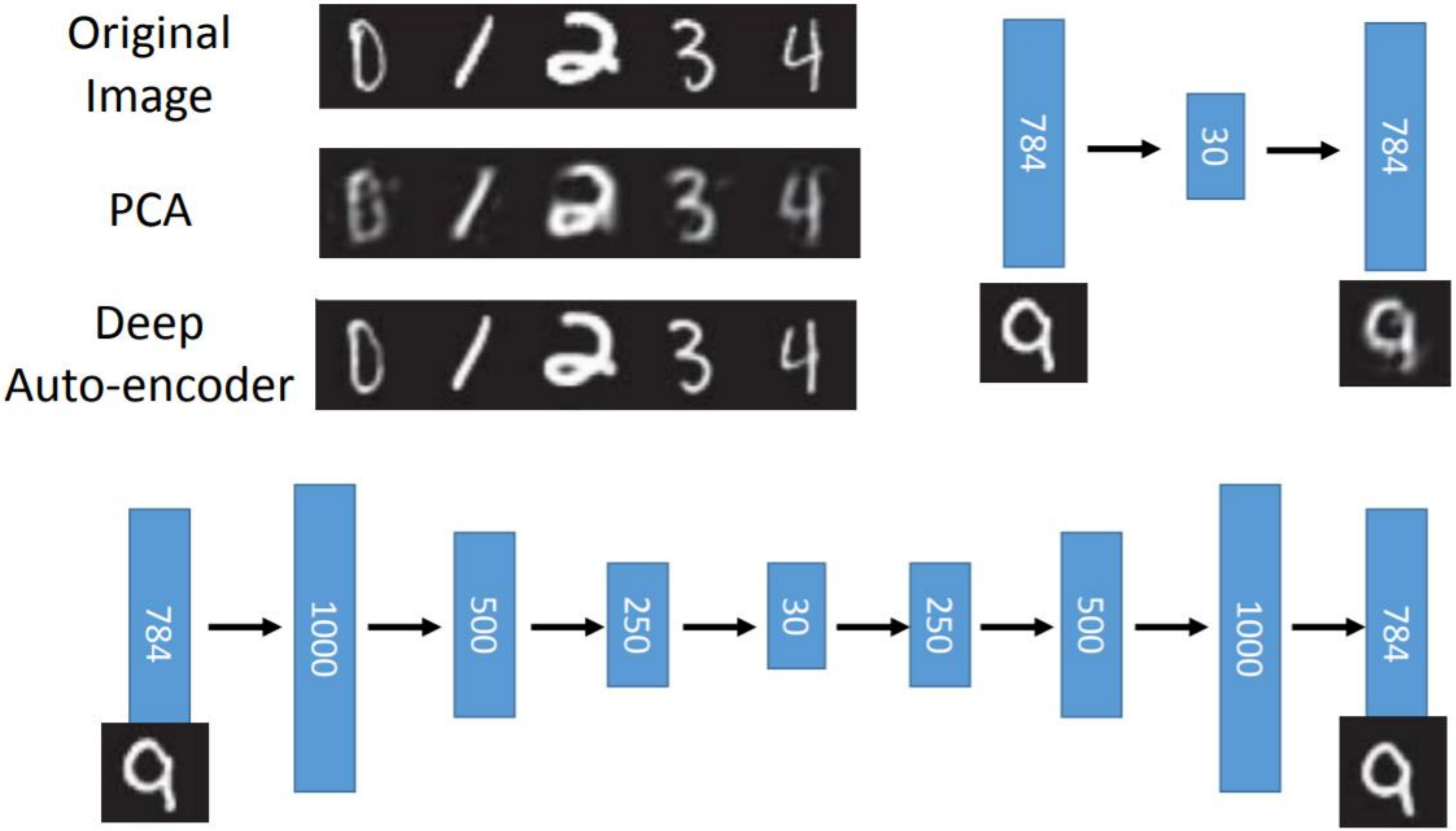
- CNN Image Classifier – Convolution section + MLP classifier
- CNN Autoencoder – Convolution section + Deconvolution section to recover the input image





Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

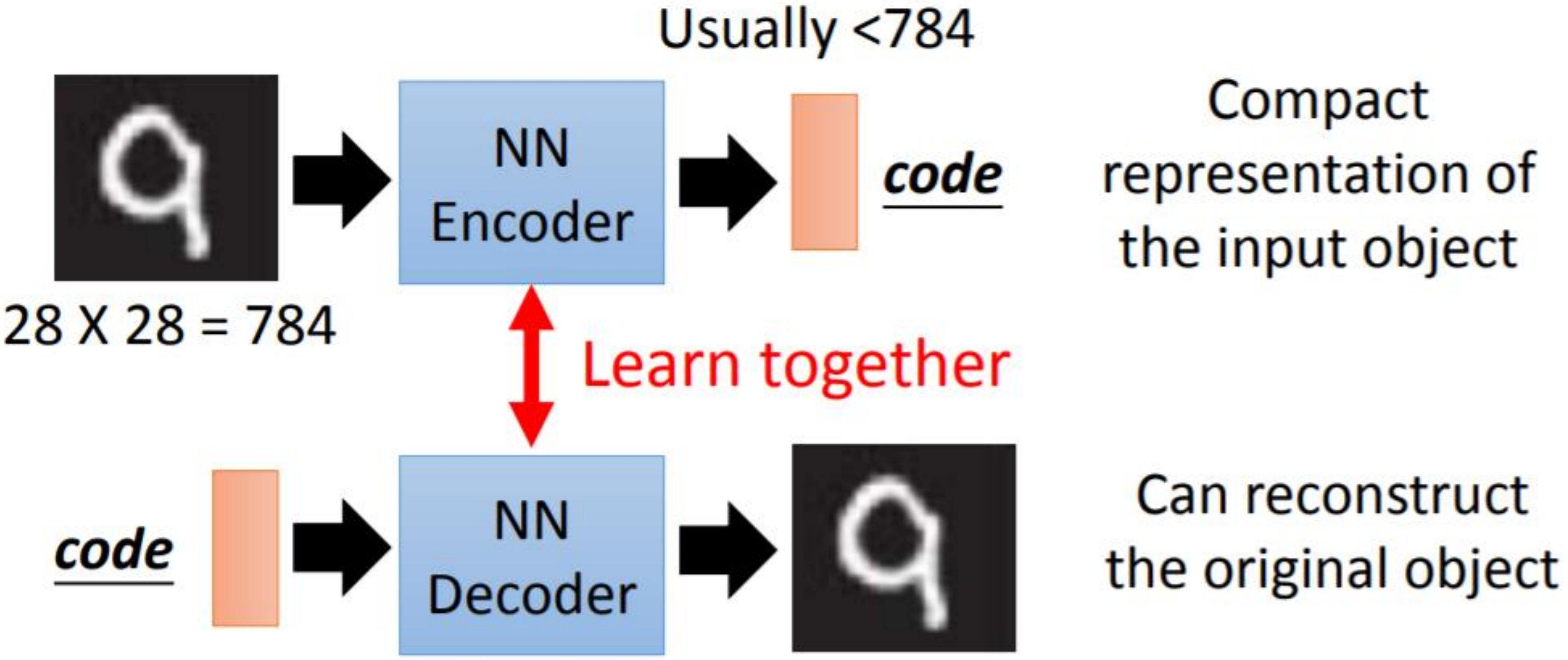
MLP based autoencoder



Reference: Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313.5786 (2006): 504-507

Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Autoencoder learns a compact representation of the input image

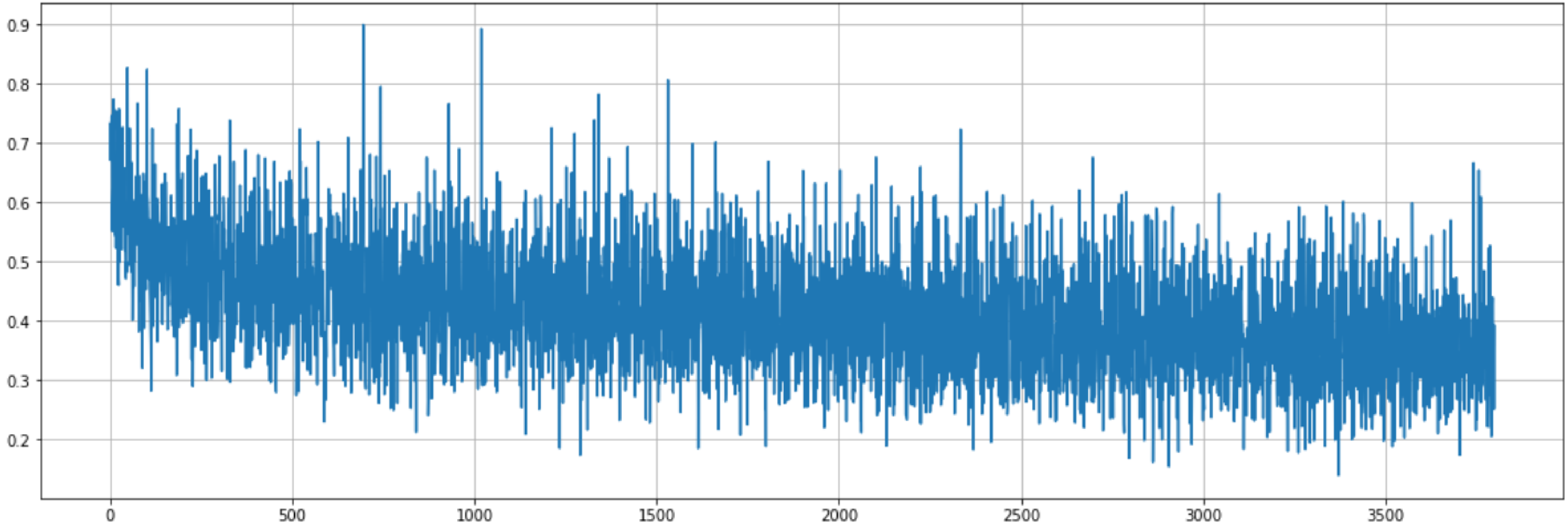


Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Practice

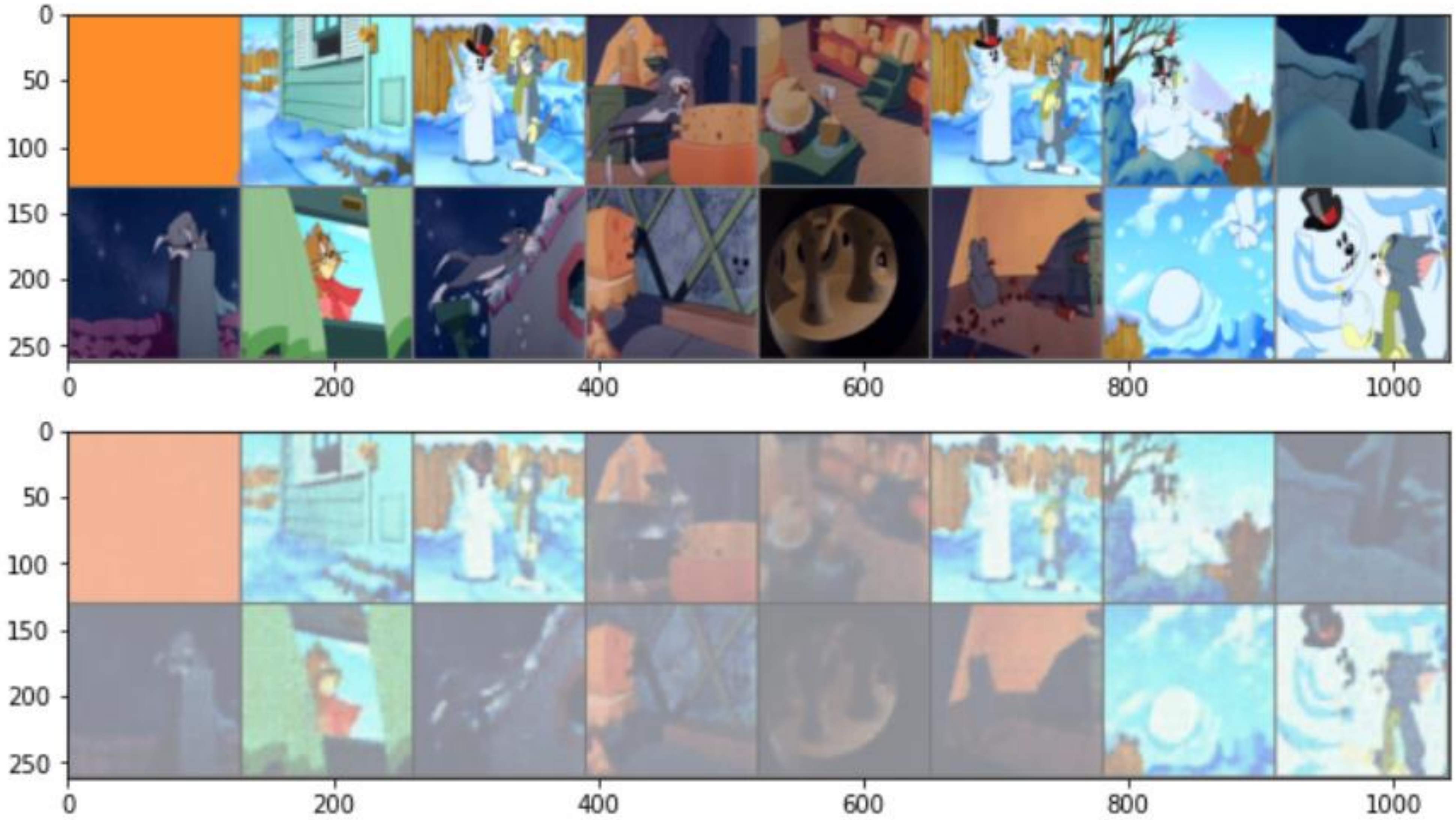
- Run “7.1.Conv_AE.ipynb"

Train 200 epochs



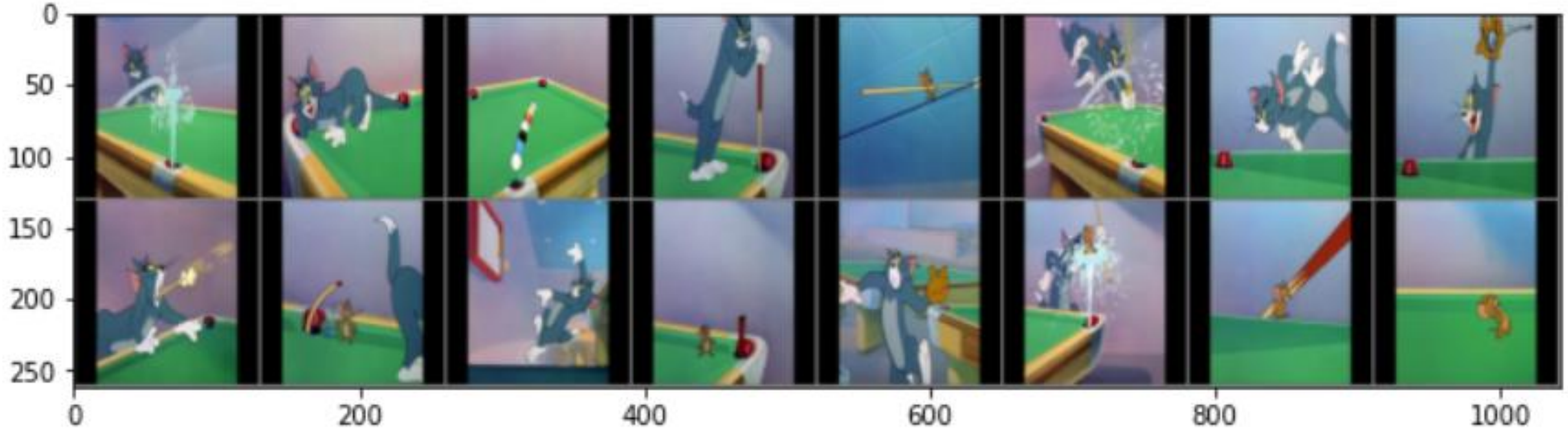
Train 200 epochs

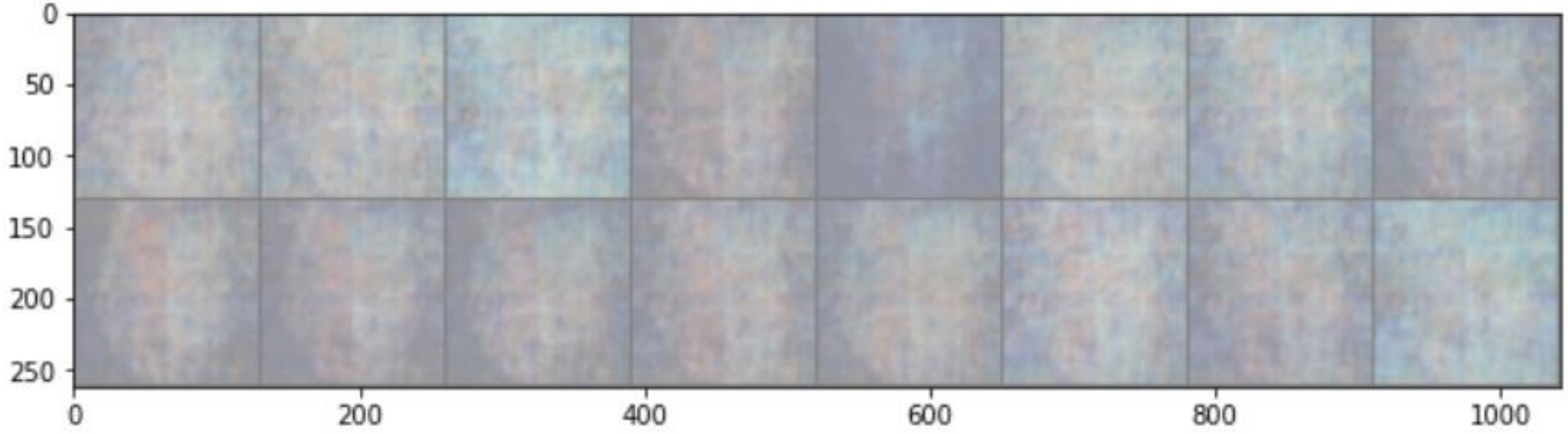
Test on training images – the NN is able to recover more from the input images



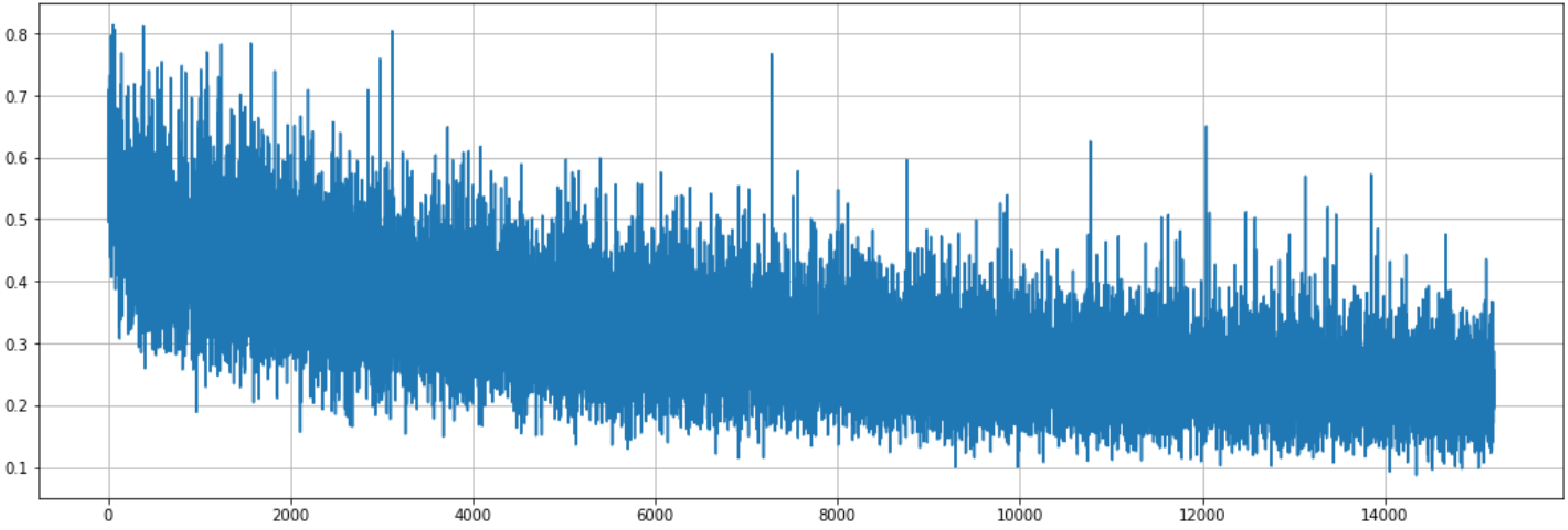
Train 200 epochs

Test on un-seen images – fails to reconstruct the input images



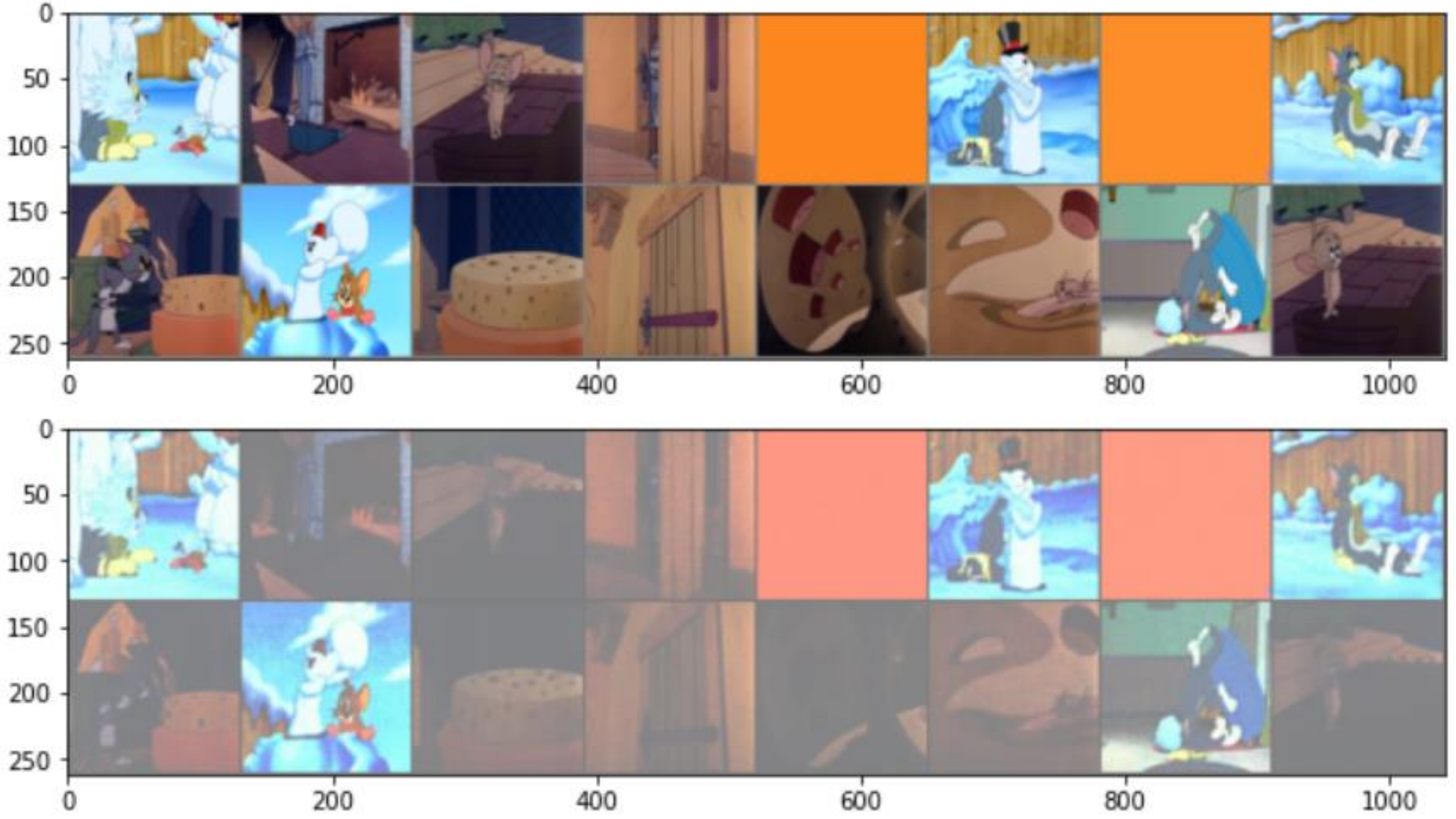


Train 800 epochs



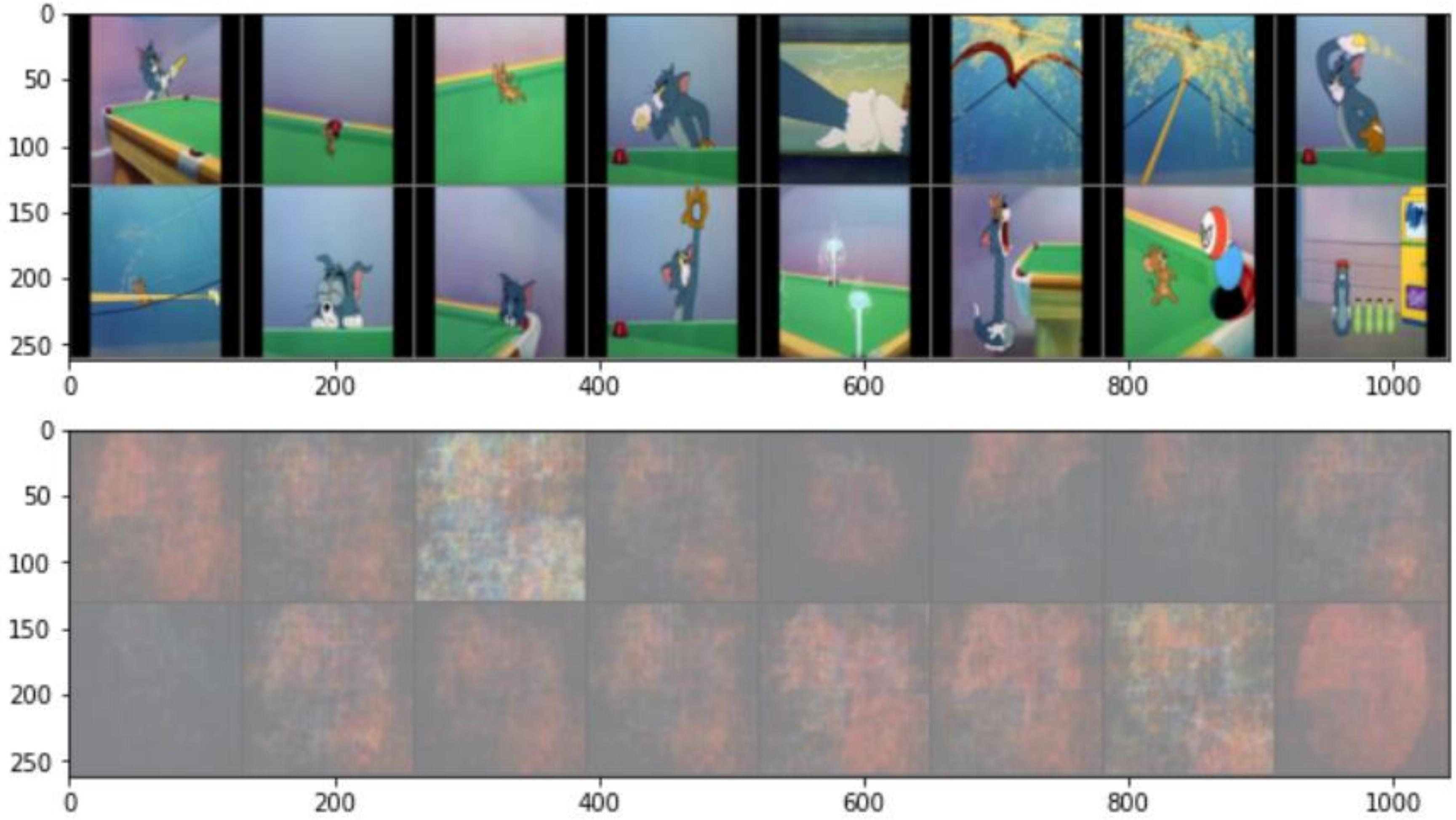
Train 800 epochs

Test on training images

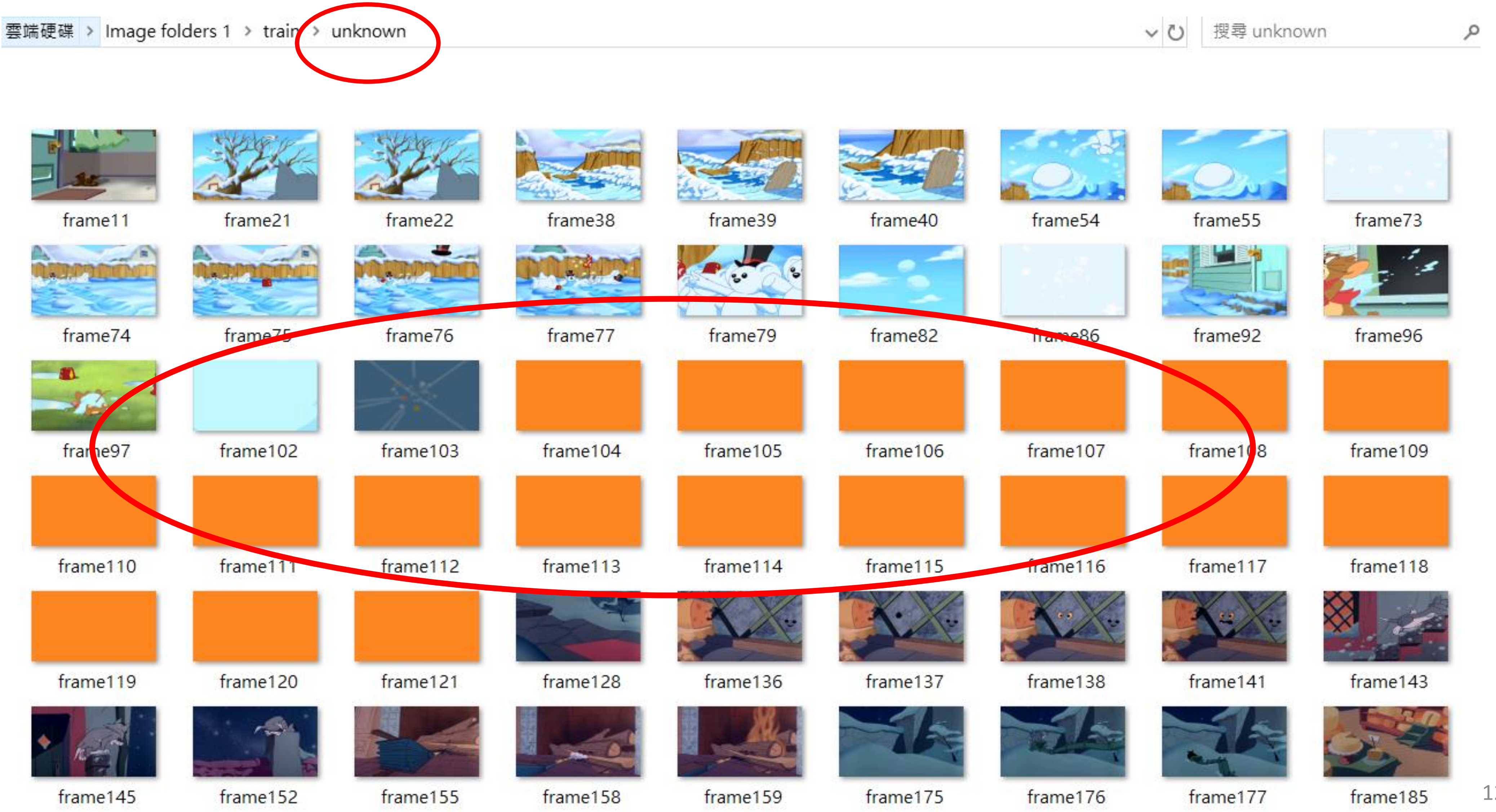


Train 800 epochs (same results when train 1200 epochs)

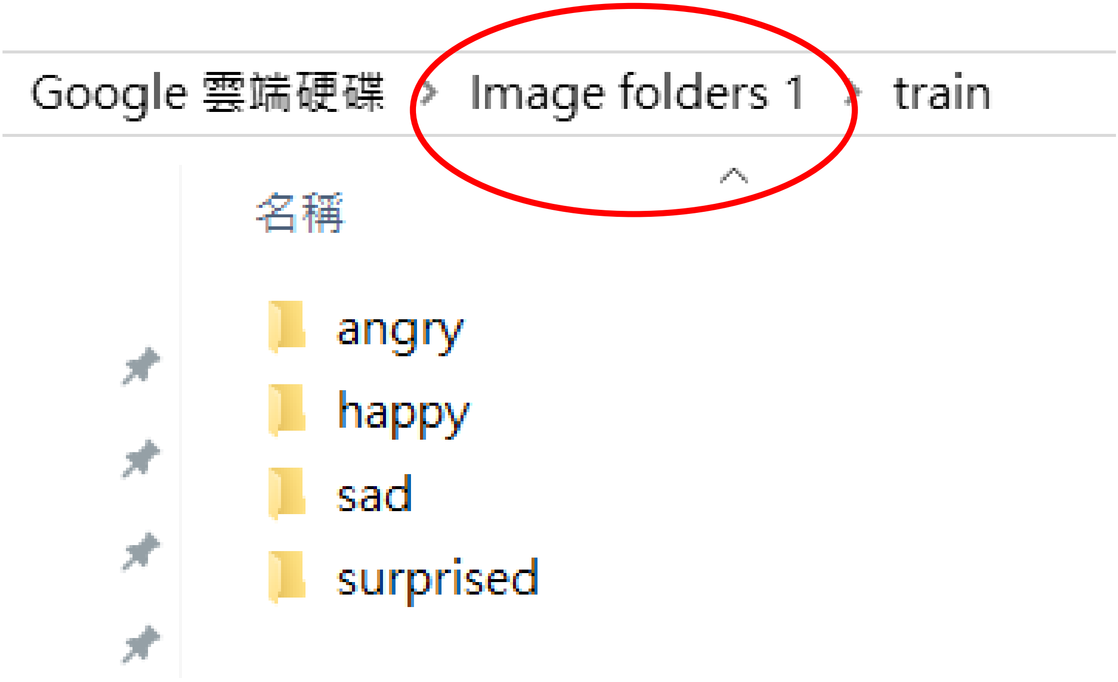
Test on un-seen images – fails to reconstruct the input images



Your AI model is as good as your data, and as bad as your data too



Create a new folder "Image folder 1", remove the "Unknown" sub-folder



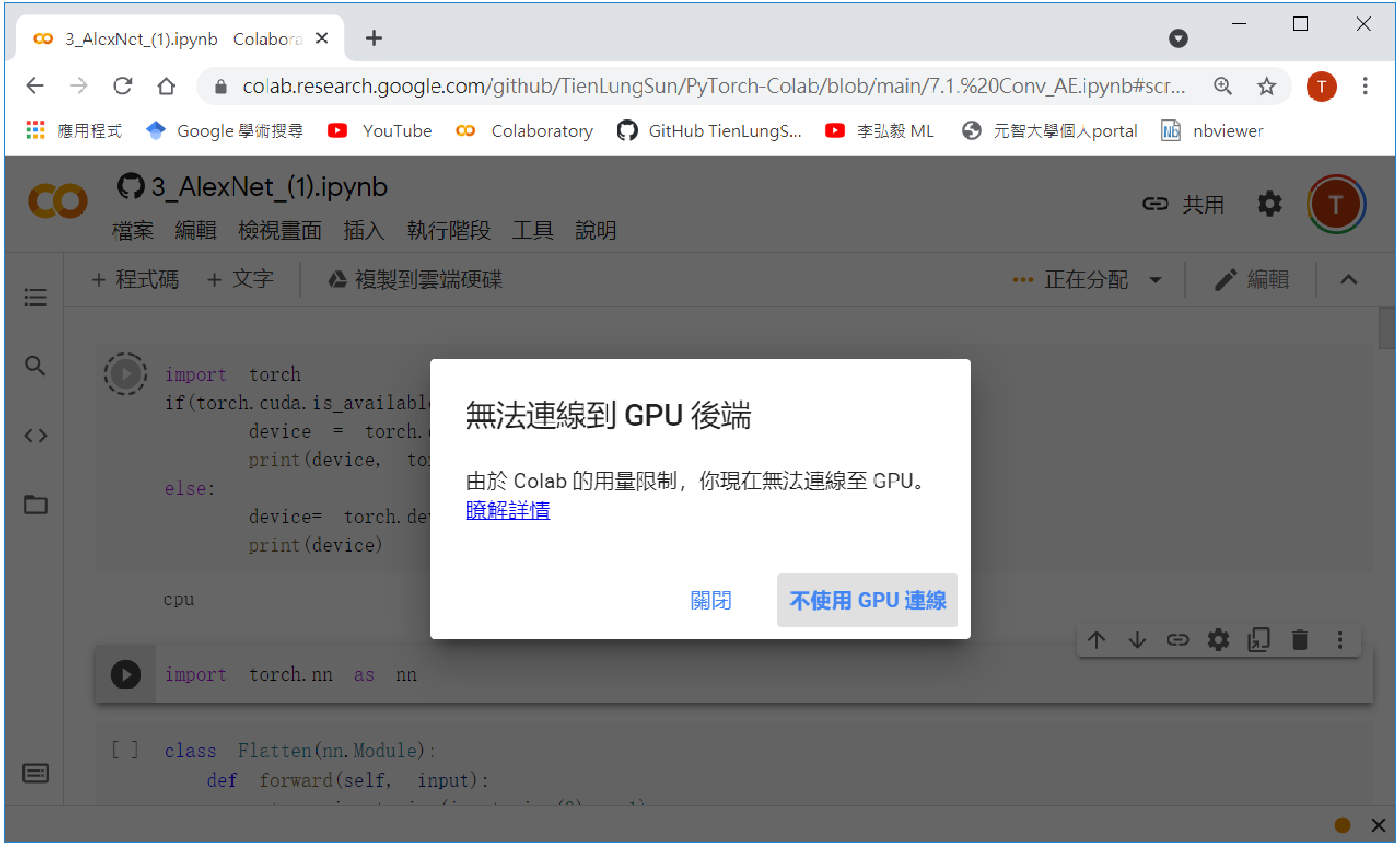
Test folder remains the same

How about batch size? Increase or decrees ?

```
self.encoder = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(32, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(64, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(128, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(256, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(512, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  nn.Conv2d(1024, 1024, kernel_size=2, stride=2)
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  Flatten(),
  nn.Linear(in_features=i, out_features=o),
)
```

```
[12]: import torch.utils.data as Data
      loader = Data.DataLoader(
          dataset=train_dataset,
          batch_size=16,
          shuffle=True)
```

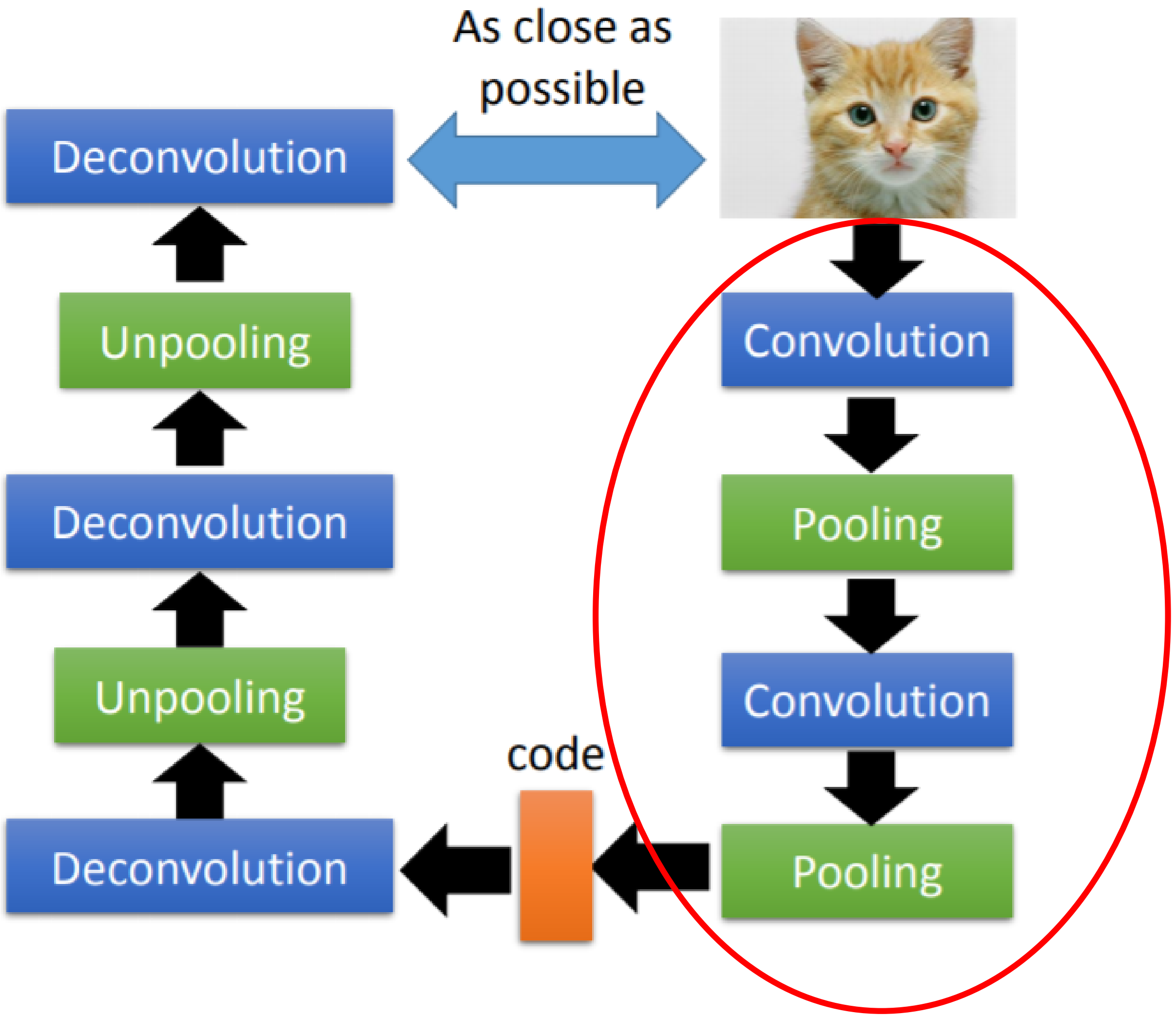
Remove the "unknown" folder and try again, but ...



Train 1200 epochs after removing the "unknown" folder

I will try later ! It's impossible
to train CNN without GPU

Encoder




```
self.encoder = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(32, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(64, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(128, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(256, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(512, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  nn.Conv2d(1024, 1024, kernel_size=2, stride=2)
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  Flatten(),
  nn.Linear(in_features=i, out_features=o),
)
```

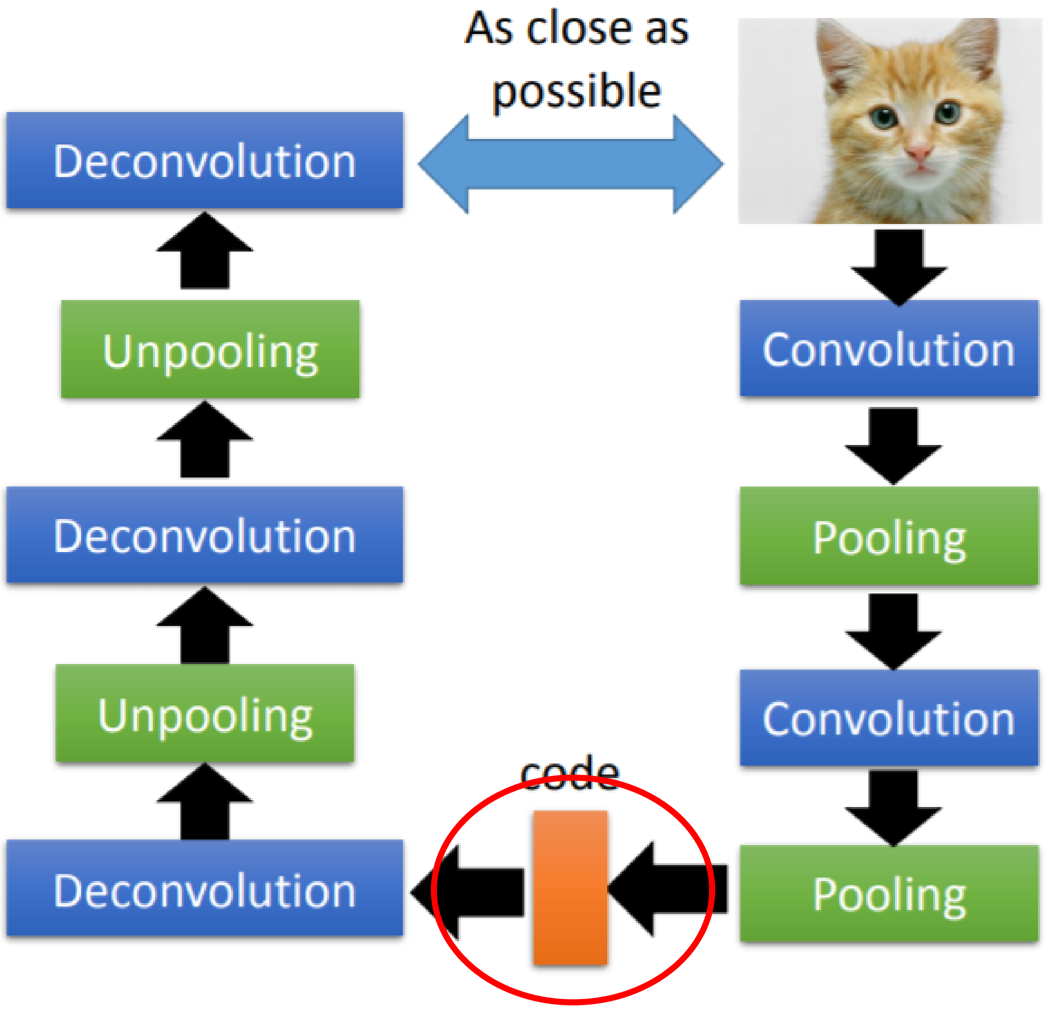
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Practice: Draw the feature maps of encoder

- Let input image = 224x224x3
- Draw the feature maps (H, W, depth) after each convolution and max pooling
- What is the number of nodes after flatten?

PYTORCH

Latent vector

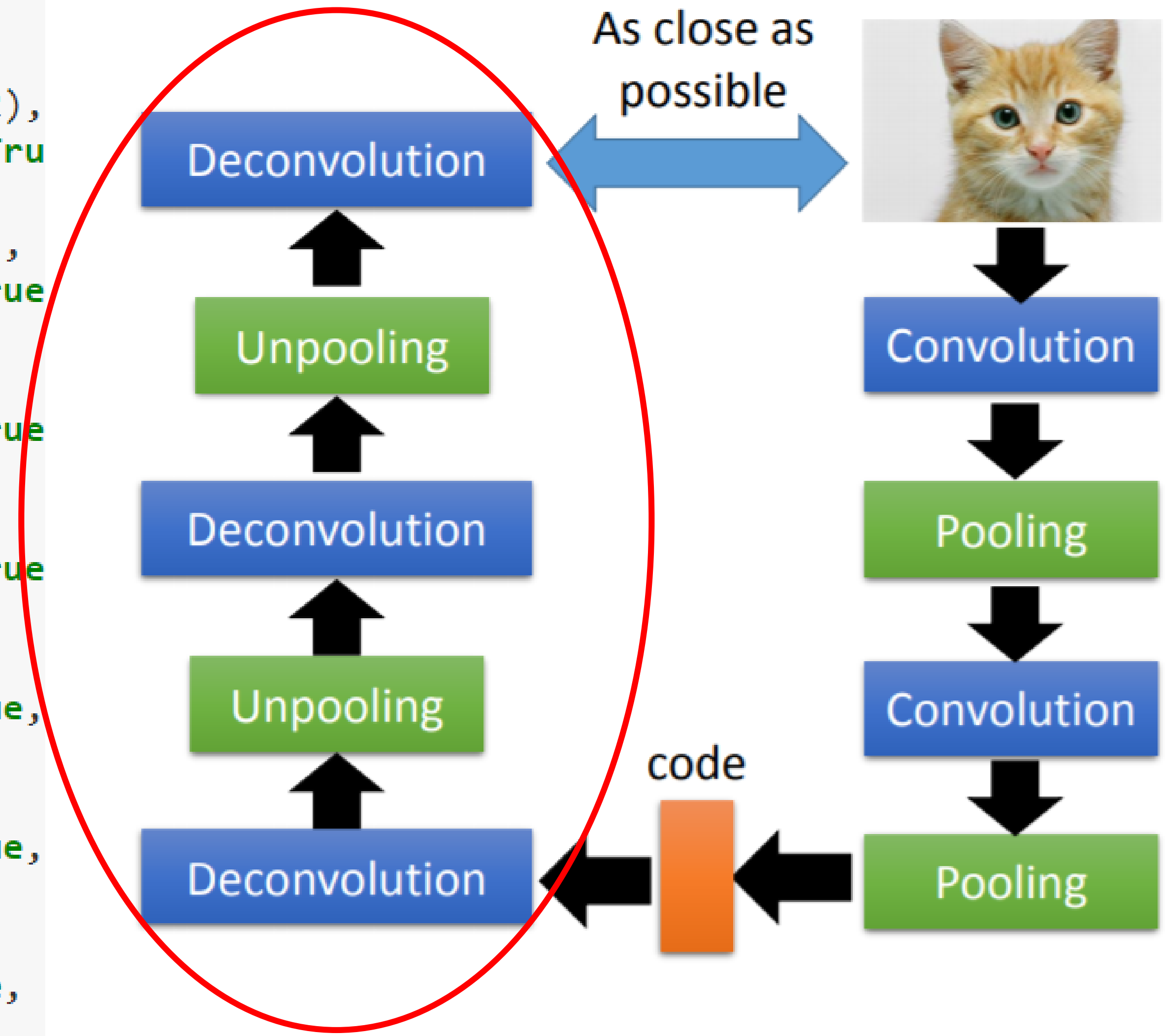



```
Flatten-22                  [-1, 1024]
 Linear-23                    [-1, 64]
 Linear-24                  [-1, 1024]
UnFlatten-25          [-1, 1024, 1, 1]
```

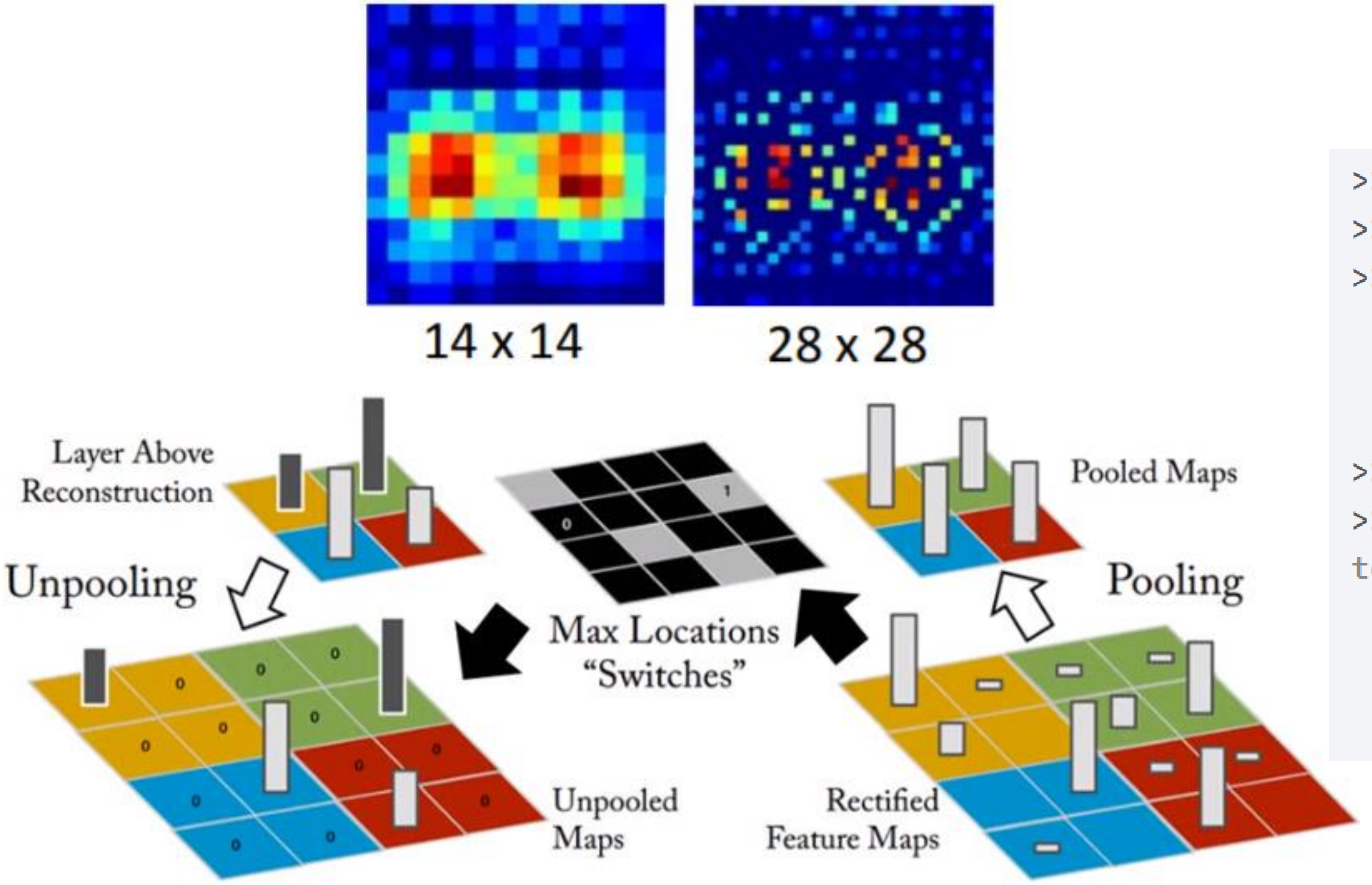
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Decoder

```
self.decoder = nn.Sequential(
  nn.Linear(in_features=o, out_features=i),
  UnFlatten(),
  nn.ConvTranspose2d(1024, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=Tru
  nn.ReLU(),
  nn.ConvTranspose2d(1024, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(512, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(256, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(128, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(64, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(32, 3, kernel_size=2, stride=2),
  nn.BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True,
  nn.Sigmoid(),
)
```



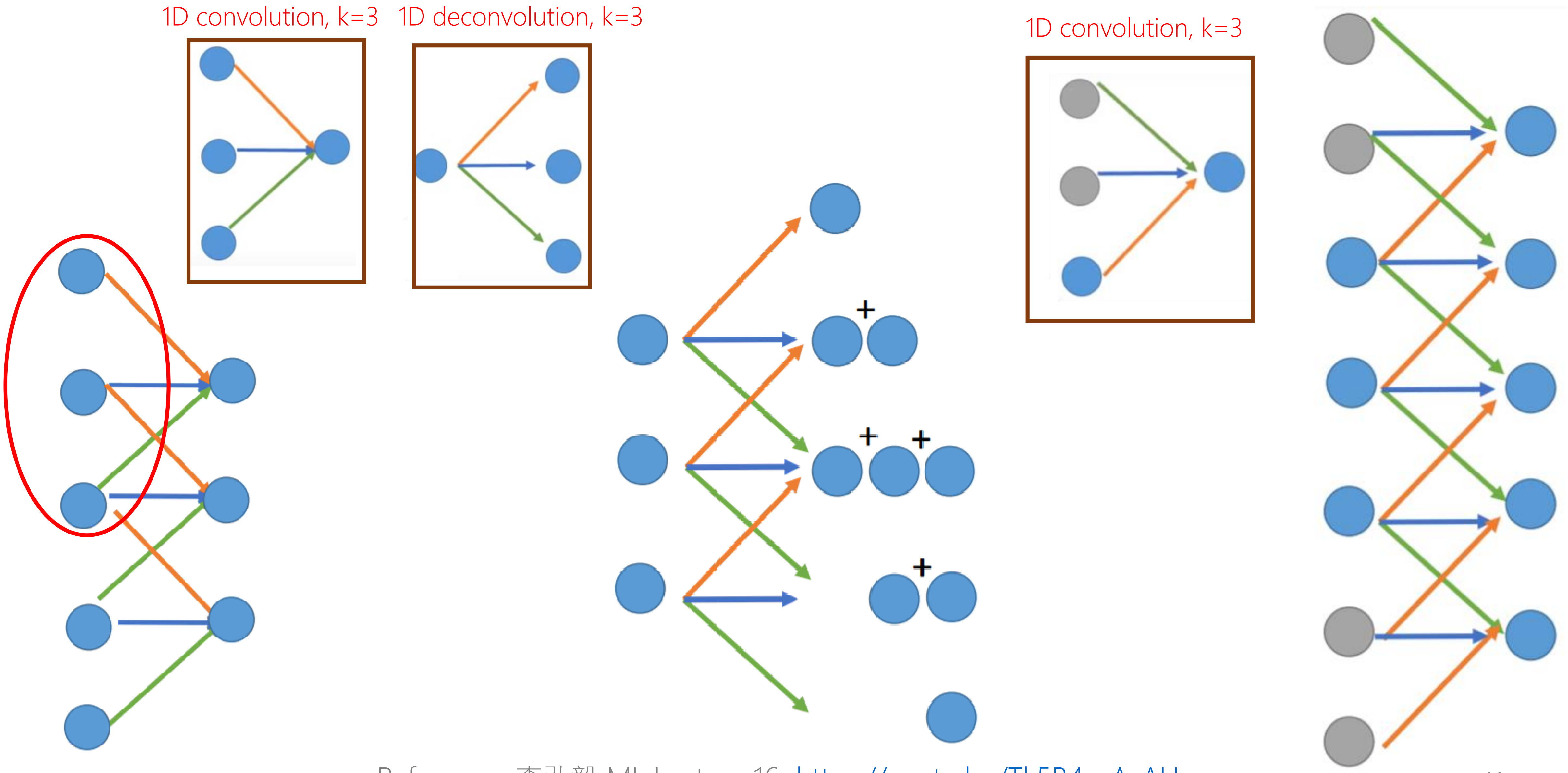
Unpooling




```
>>> pool = nn.MaxPool2d(2, stride=2, return_indices=True)
>>> unpool = nn.MaxUnpool2d(2, stride=2)
>>> input = torch.tensor([[[[ 1.,  2,  3,  4],
                            [ 5,  6,  7,  8],
                            [ 9, 10, 11, 12],
                            [13, 14, 15, 16]]]])
>>> output, indices = pool(input)
>>> unpool(output, indices)
tensor([[[[  0.,   0.,   0.,   0.],
          [  0.,   6.,   0.,   8.],
          [  0.,   0.,   0.,   0.],
          [  0.,  14.,   0.,  16.]]]])
```

Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Deconvolution



Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

In this ConvAE example, we only use deconvolution for up sampling, no un-pooling is used.

```
self.decoder = nn.Sequential(
  nn.Linear(in_features=o, out_features=i),
  UnFlatten(),
  nn.ConvTranspose2d(1024, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=Tru
  nn.ReLU(),
  nn.ConvTranspose2d(1024, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(512, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(256, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(128, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(64, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(32, 3, kernel_size=2, stride=2),
  nn.BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True,
  nn.Sigmoid(),
)
```

Practice: Draw the feature maps of decoder

- Input – the number of nodes after un-flattern
- Draw feature maps (H, W, depth) after each de-convolution and un-max pooling

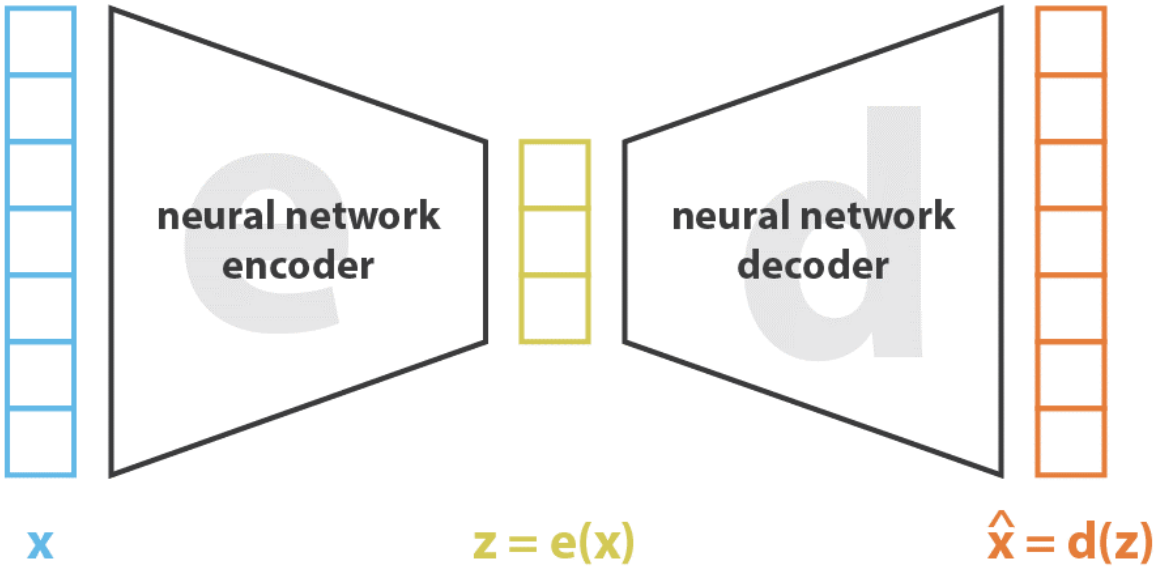
PYTORCH

Deconvolution

```
(2): ConvTranspose2d(1024, 1024, kernel_size=(2, 2), stride=(2, 2))
(3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_r
(4): ReLU()
(5): ConvTranspose2d(1024, 512, kernel_size=(2, 2), stride=(2, 2))
(6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_ru
(7): ReLU()
(8): ConvTranspose2d(512, 256, kernel_size=(2, 2), stride=(2, 2))
(9): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_ru
(10): ReLU()
```

```
   ConvTranspose2d-26          [-1, 1024, 2, 2]
       BatchNorm2d-27          [-1, 1024, 2, 2]
              ReLU-28          [-1, 1024, 2, 2]
   ConvTranspose2d-29           [-1, 512, 4, 4]
       BatchNorm2d-30           [-1, 512, 4, 4]
              ReLU-31           [-1, 512, 4, 4]
   ConvTranspose2d-32           [-1, 256, 8, 8]
       BatchNorm2d-33           [-1, 256, 8, 8]
              ReLU-34           [-1, 256, 8, 8]
   ConvTranspose2d-35         [-1, 128, 16, 16]
       BatchNorm2d-36         [-1, 128, 16, 16]
              ReLU-37         [-1, 128, 16, 16]
   ConvTranspose2d-38          [-1, 64, 32, 32]
       BatchNorm2d-39          [-1, 64, 32, 32]
              ReLU-40          [-1, 64, 32, 32]
```

Loss function



$$\text{loss} = \|x - \hat{x}\|^2 = \|x - d(z)\|^2 = \|x - d(e(x))\|^2$$

Source: https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

[13]:
```
for batchX, _ in loader:
  break;
print(batchX.shape)
```

```
torch.Size([16, 3, 128, 128])
```

[14]:
```
tensorY=model(batchX.to(device))
print(tensorY.shape)
```

```
torch.Size([16, 3, 128, 128])
```

[15]:
```
loss = loss_func(tensorY, batchX.to(device))
print(loss)
```

```
tensor(0.6961, device='cuda:0', grad_fn=<Msel
```

HW6 (1)

- Train an AE to learn a compact representation (try latent vector of size 20, 30, 50) of your facial expression. Test with 10 happy and 10 angry faces.
- Show the recovered image.
- Send the latent vectors to *t*-SNE to see whether they form clusters.

Save and load PyTorch model

```
[27]: torch.save(model.state_dict(), "AE800.pt")
```

```
[28]: model=autoencoder() #build NN architecture
      model.load_state_dict(torch.load("AE800.pt")) #load model weights
      model.to(device)
      model.eval()
```

PYTORCH

Save and load PyTorch model

Get latent vectors of all training images

```
[37]: for step, (batchX, batchY) in enumerate(loader):
        tensorY = model.encoder(batchX.to(device))
        if(step==0):
          arrayX = np.array(tensorY.cpu().detach().numpy())
          arrayY = batchY.cpu().detach().numpy()
        else:
          arrayX = np.concatenate((arrayX, tensorY.cpu().detach().numpy()))
          arrayY = np.concatenate((arrayY, batchY.cpu().detach().numpy()))
      print(arrayX.shape, arrayY.shape)
```

```
(298, 64) (298,)
```

Use *t*-SNE to reduce dimensions from 64 to 2

[38]:
```
from sklearn.manifold import TSNE
tsne = TSNE(perplexity=5, n_components=2, init='pca', n_iter=5000)
# try perlexity = 5, 10, 30, 50
```

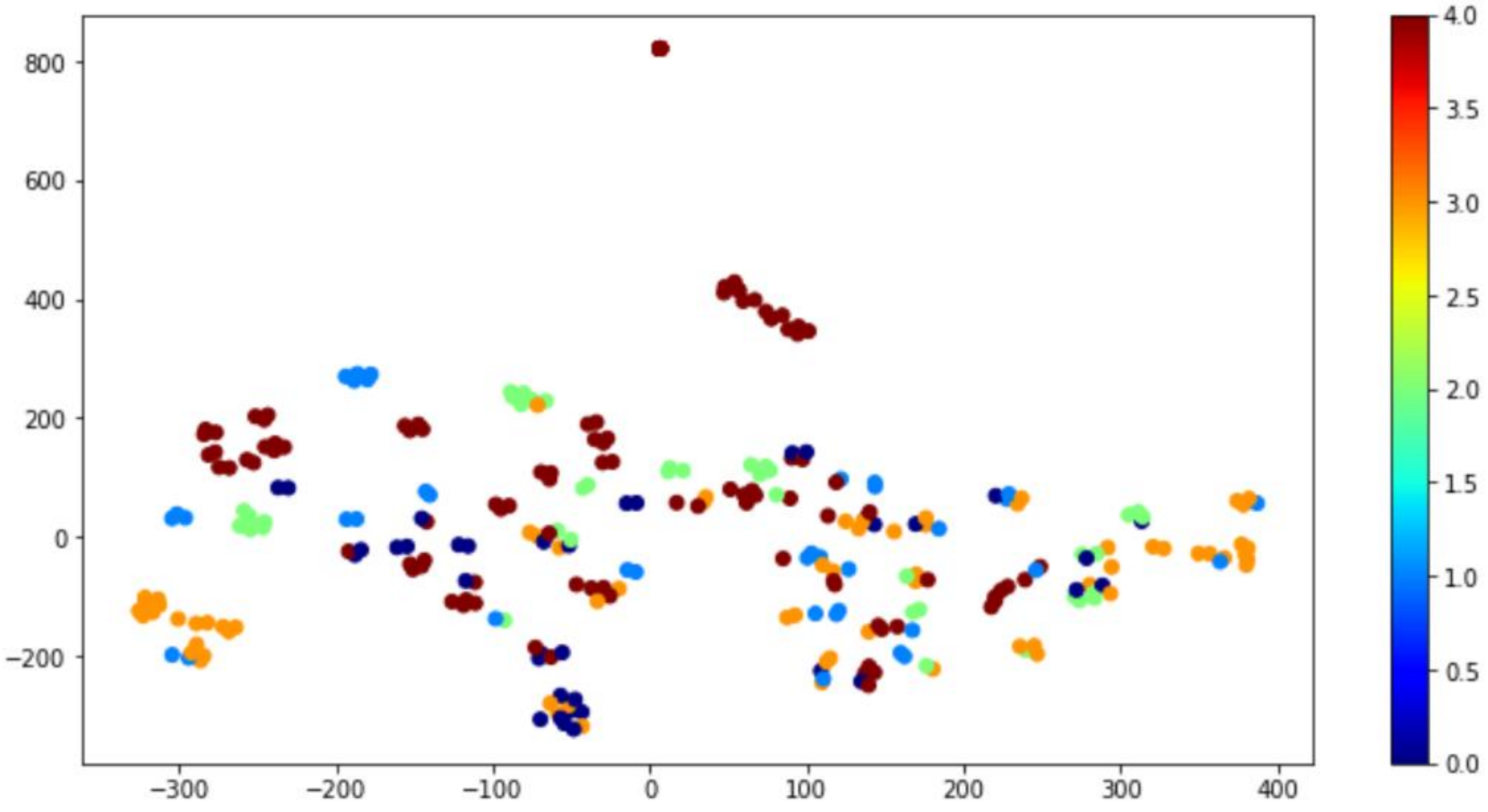
[39]:
```
x=tsne.fit_transform(arrayX)
print(x.shape)
```

```
(298, 2)
```

[40]:
```
plt.figure(figsize=(18,9))
plt.scatter(x[:, 0], x[:, 1], c= arrayY)
plt.show()
```

PYTORCH

Use *t*-SNE to reduce dimensions from 64 to 2

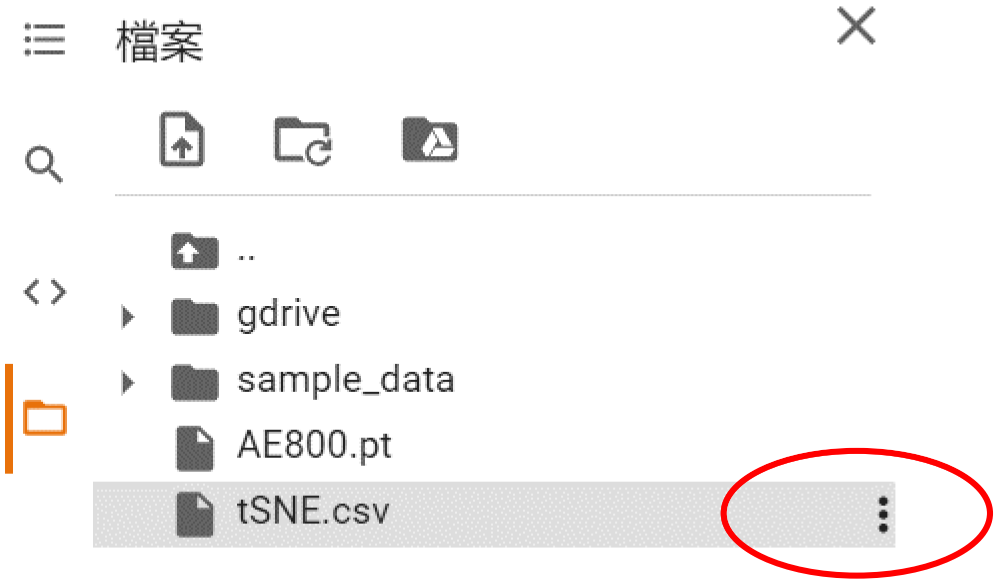


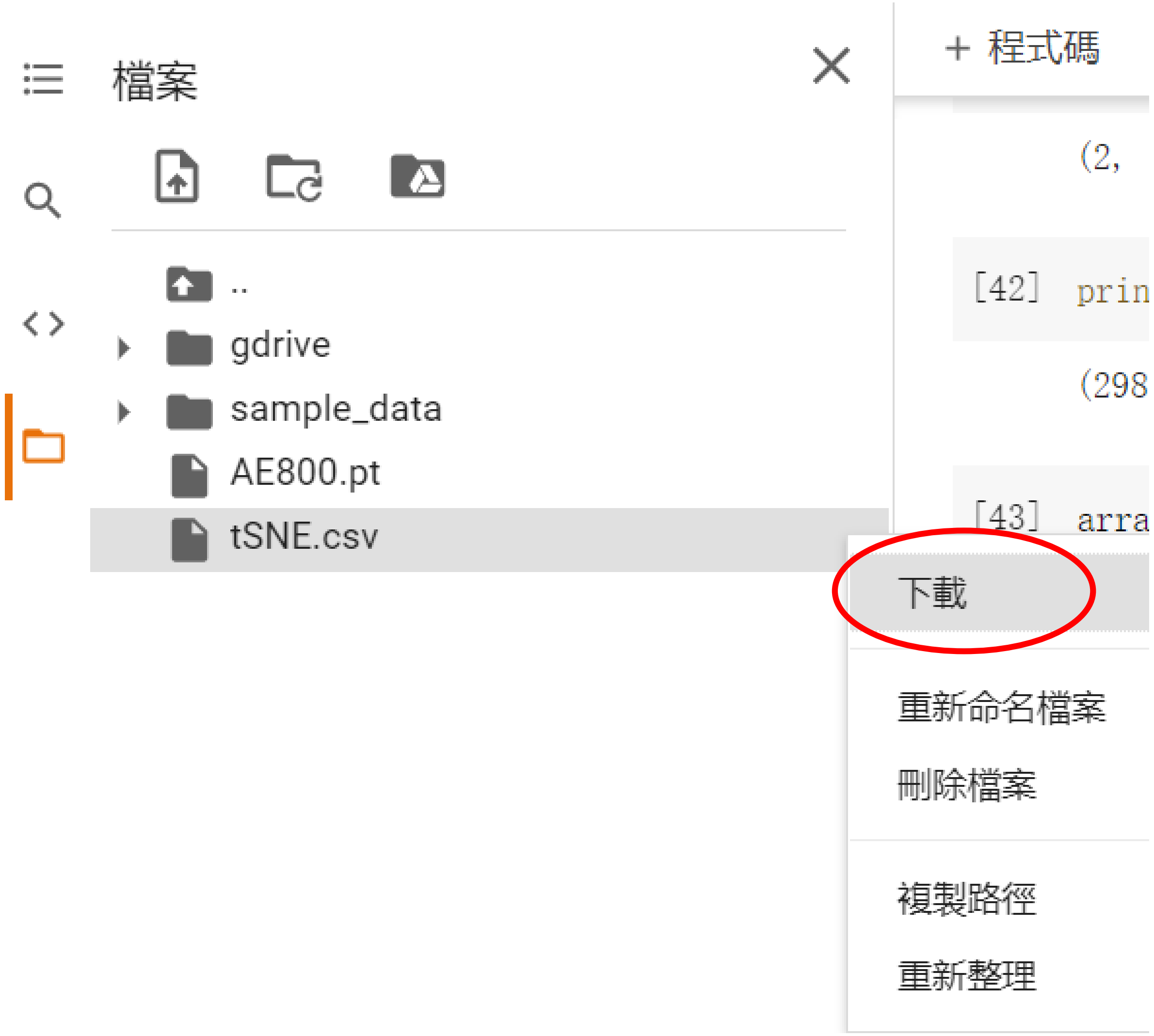
Save data to csv file

```
[42] print(x.shape, arrayY.shape)

     (298, 2) (298,)

[43] arrayY1 = arrayY.reshape(arrayY.shape[0], 1)
     print(arrayY1.shape)

     (298, 1)

[44] XYArray = np.hstack((x, arrayY1))
     print(XYArray.shape)

     (298, 3)

[45] # Save data to excel for further Tableau visualization
     import pandas as pd
     pd.DataFrame(XYArray).to_csv("tSNE.csv")
```

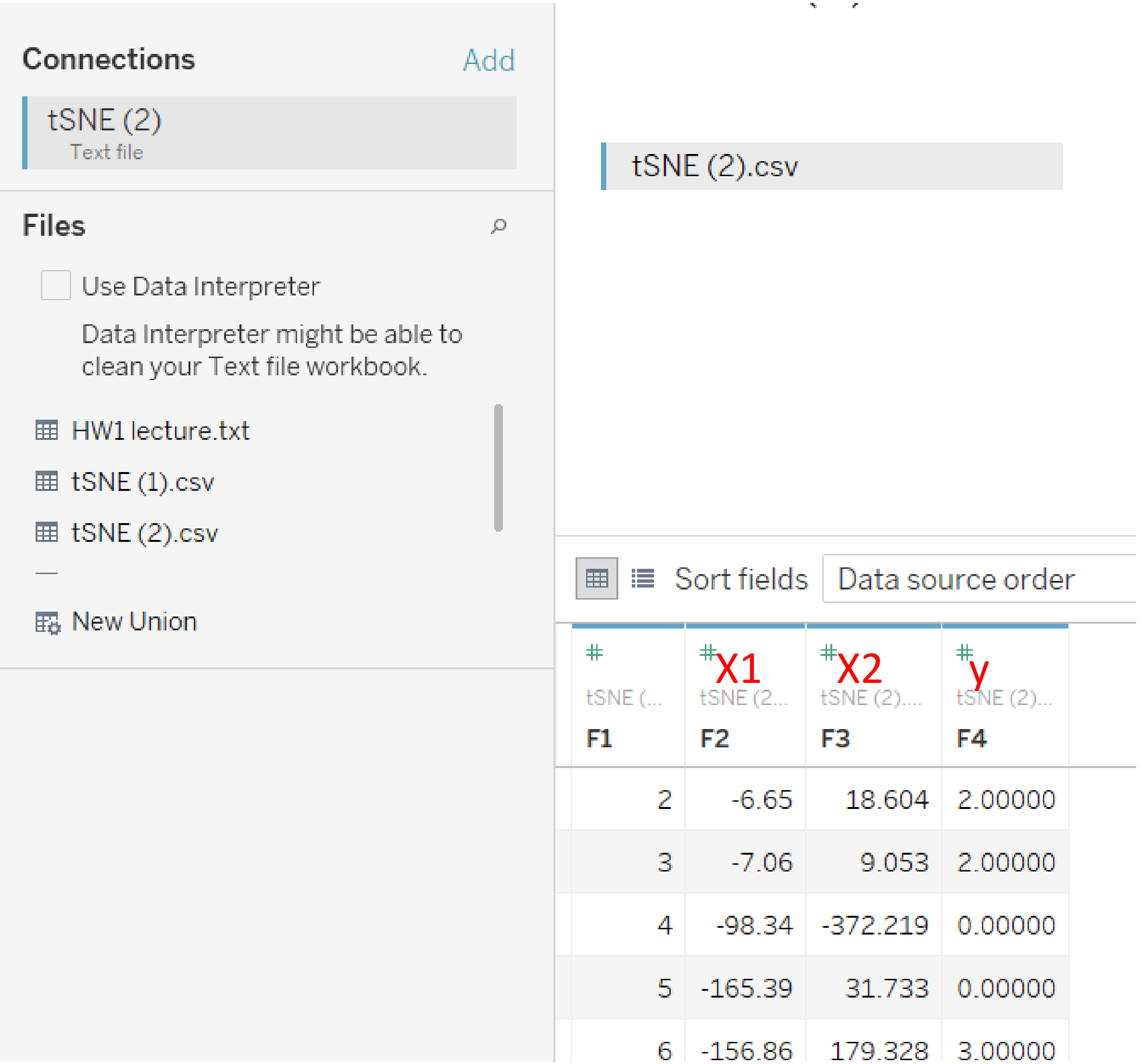
Save data to csv file

Download csv file

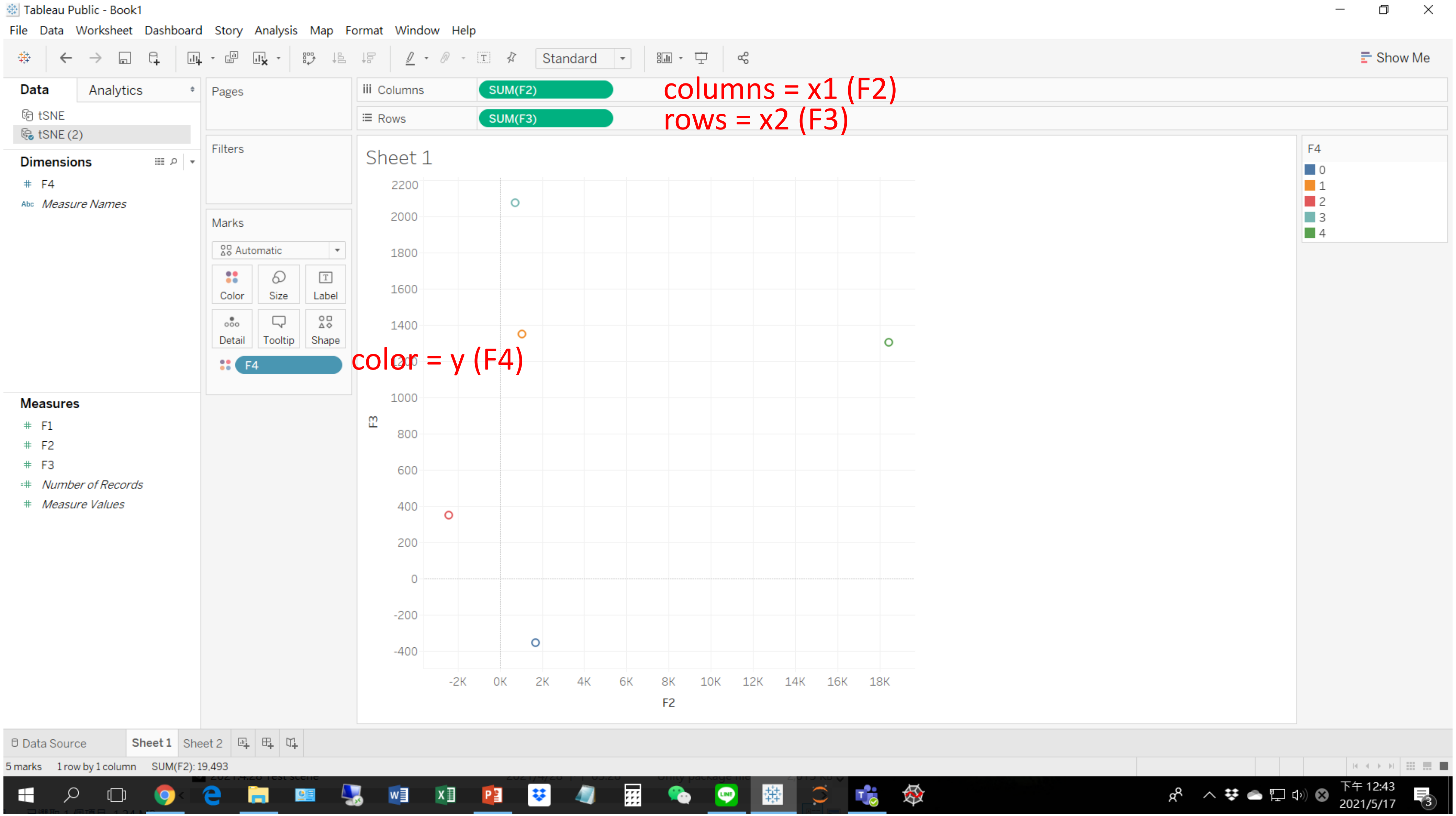




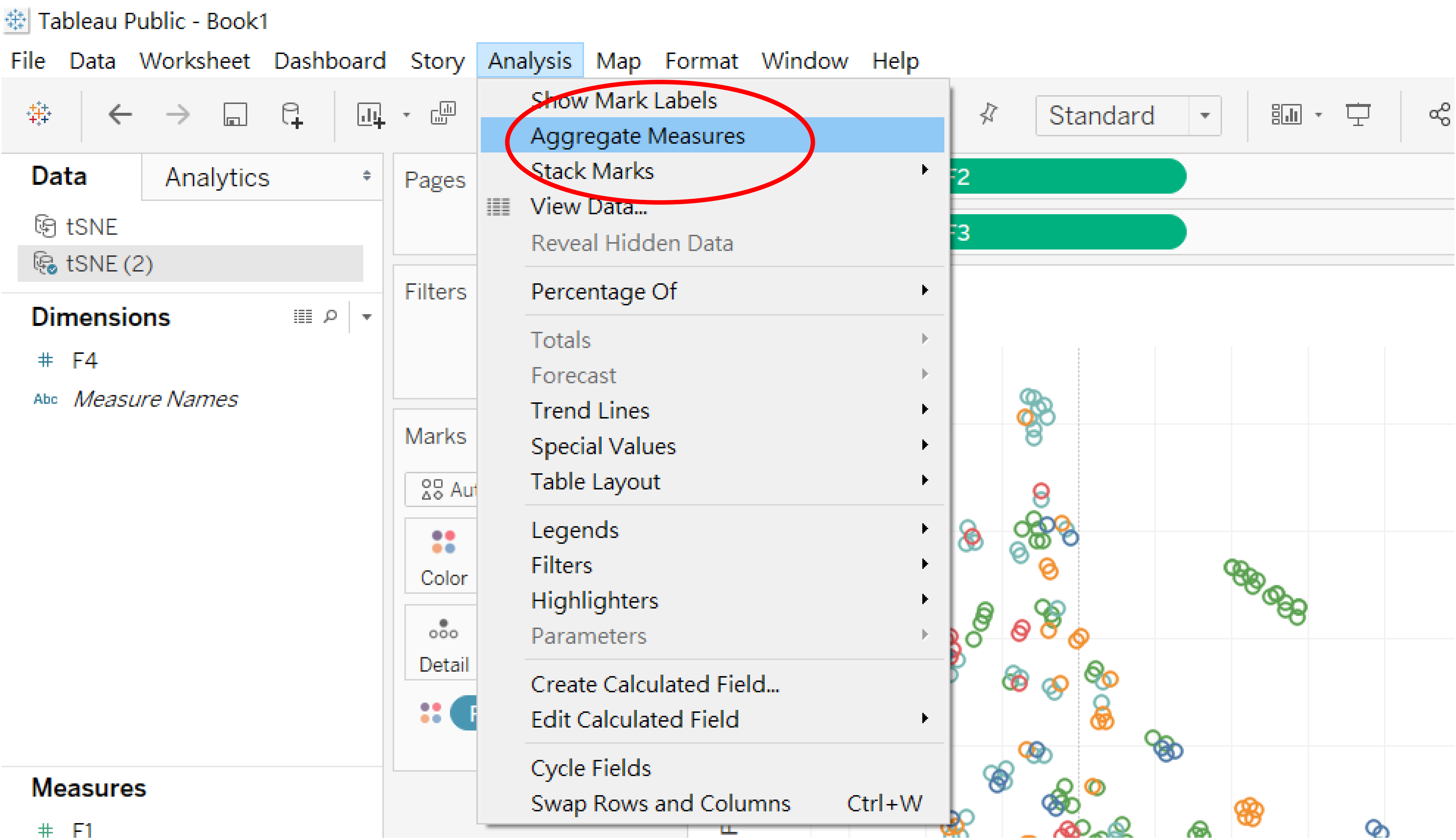
Visualize in Tableau public



Visualize in Tableau public



Visualize in Tableau public



Visualize in Tableau public