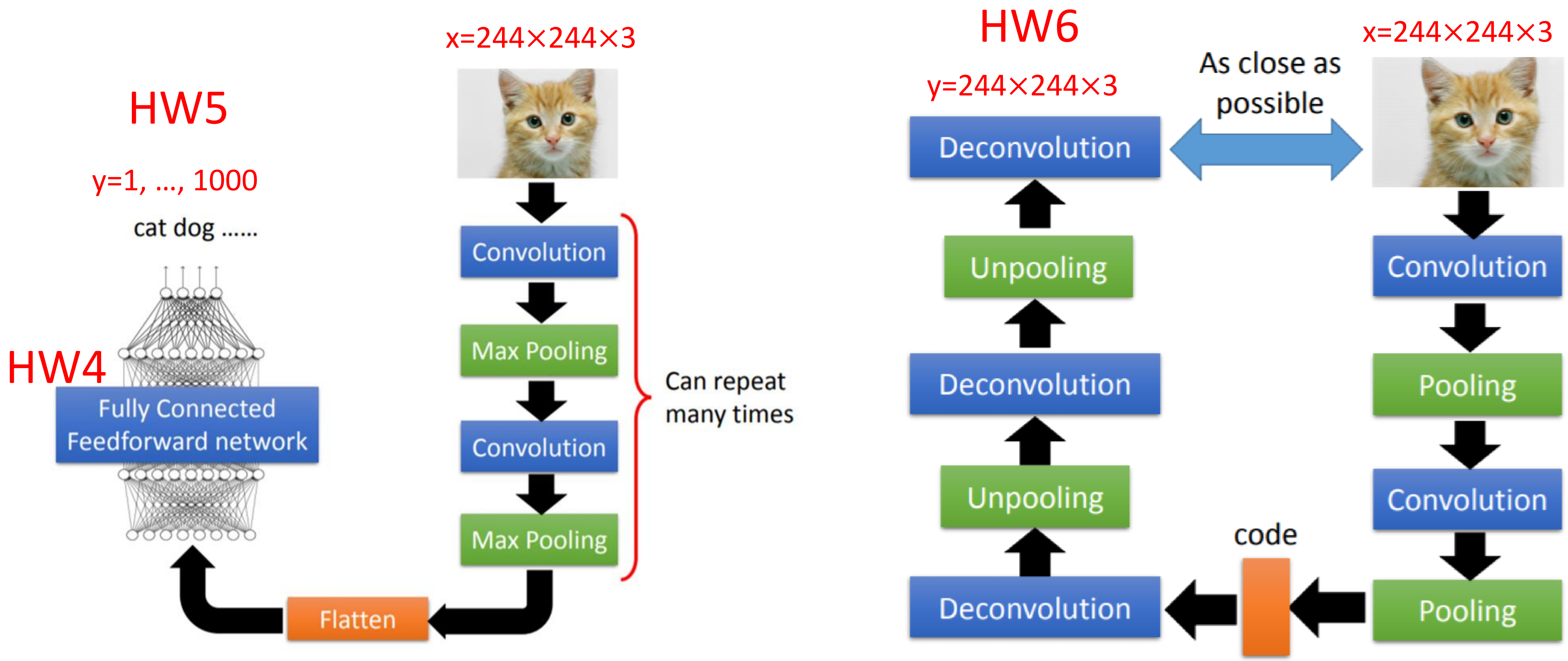
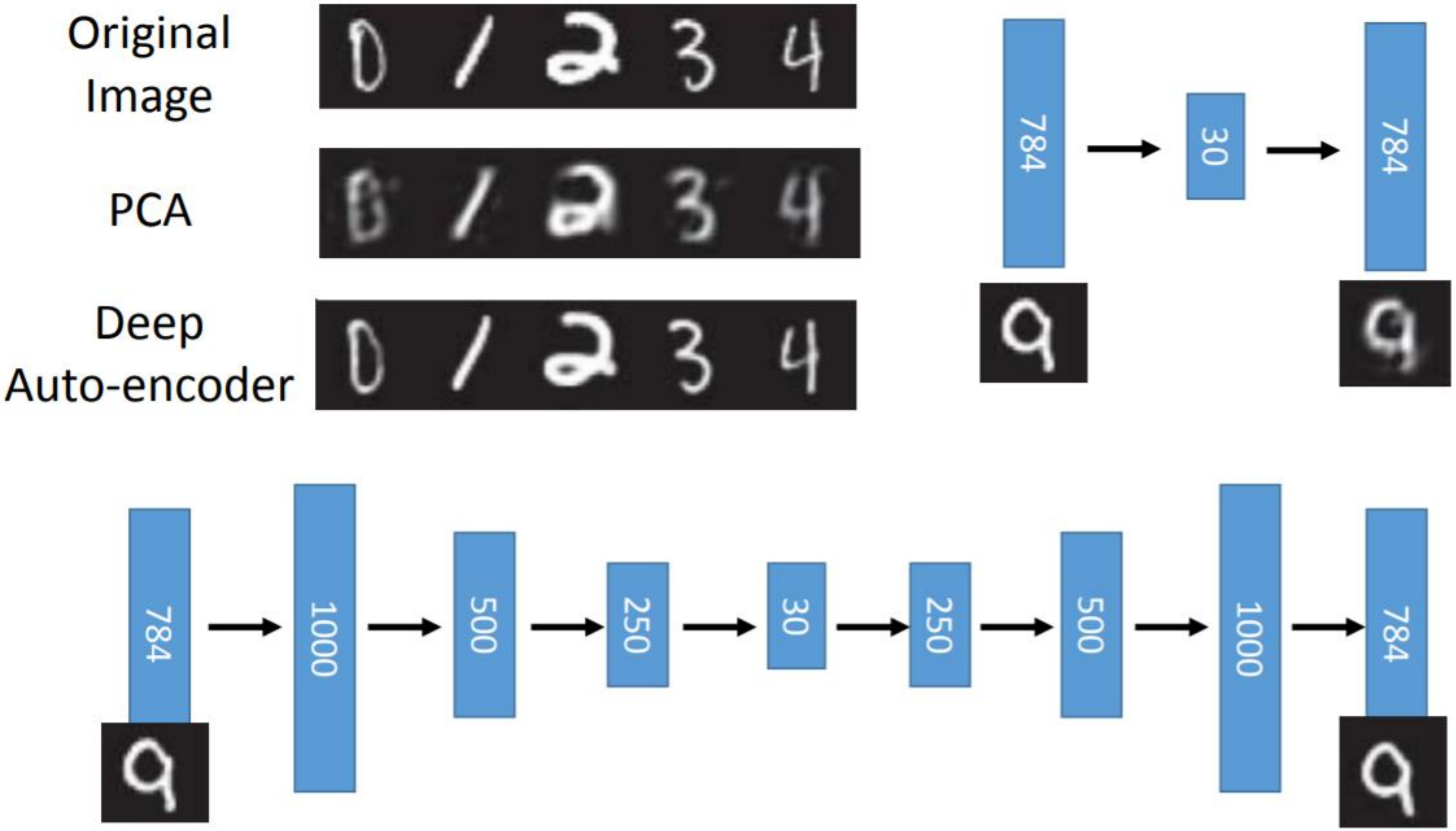
Auto-encoder

- 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

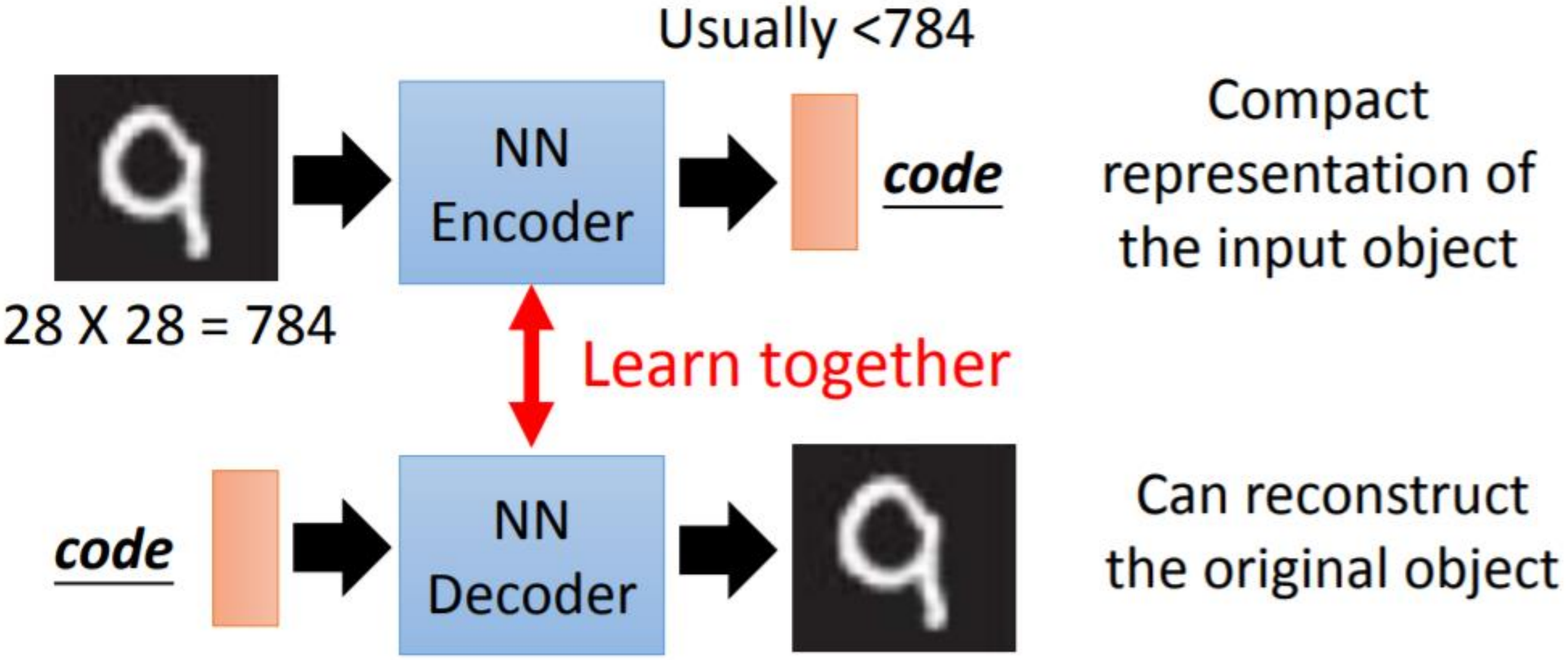
MLP based autoencoder



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

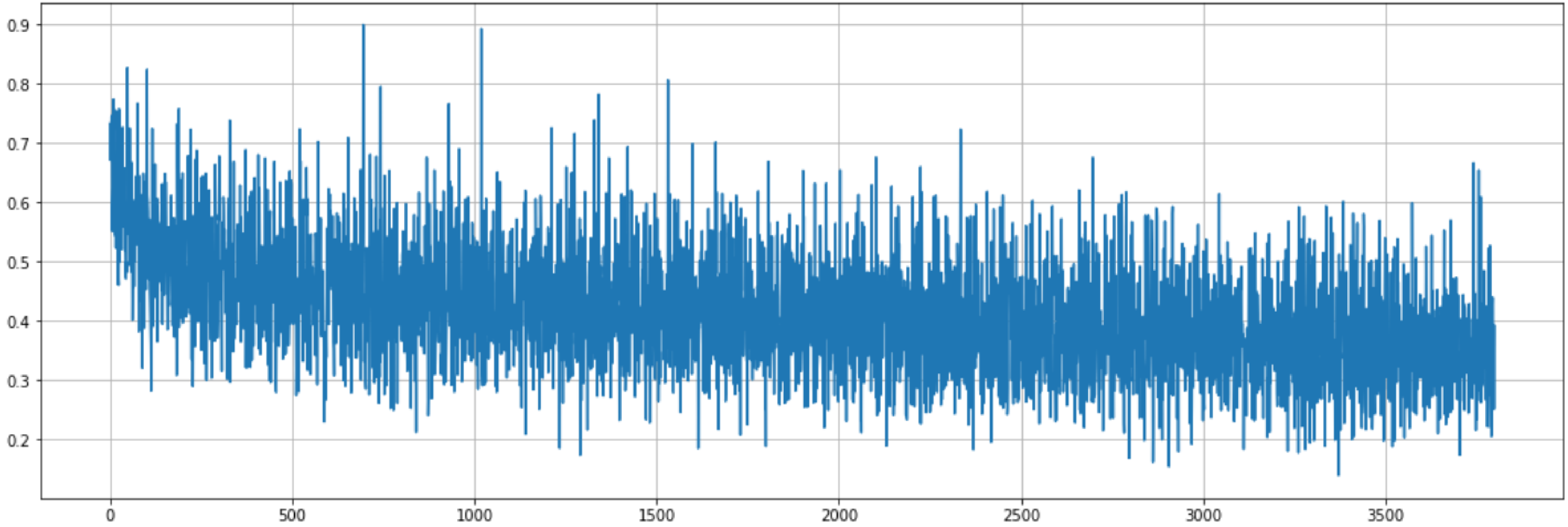


Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Practice

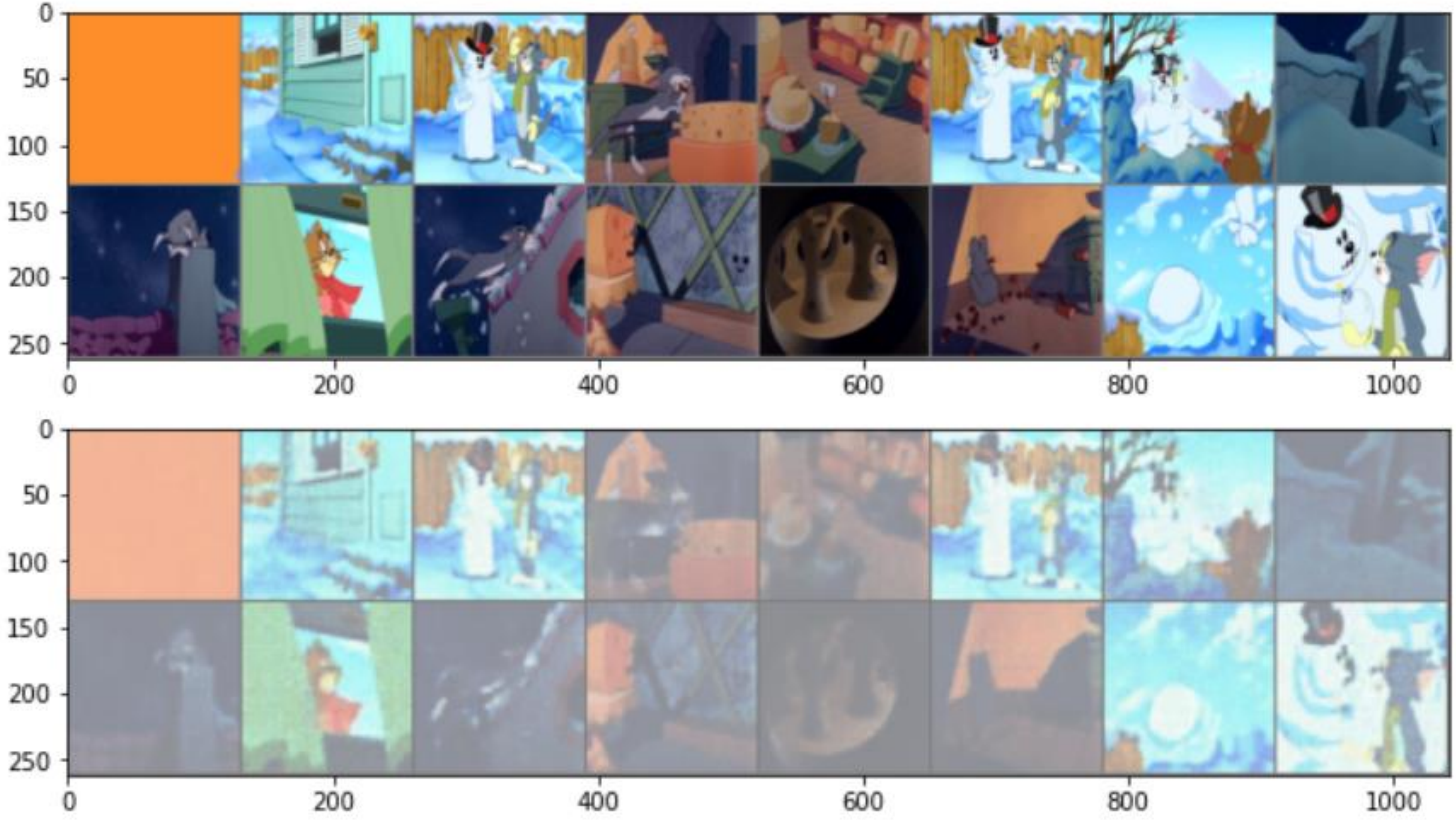
- Run “7.1.Conv_AE.ipynb"

Train 200 epochs



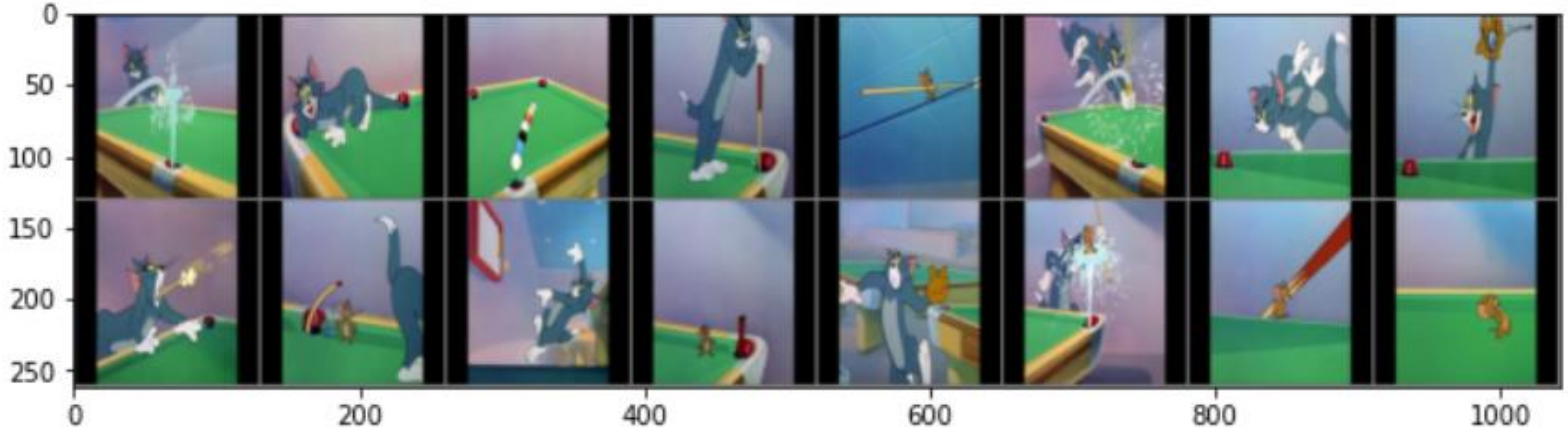
Train 200 epochs

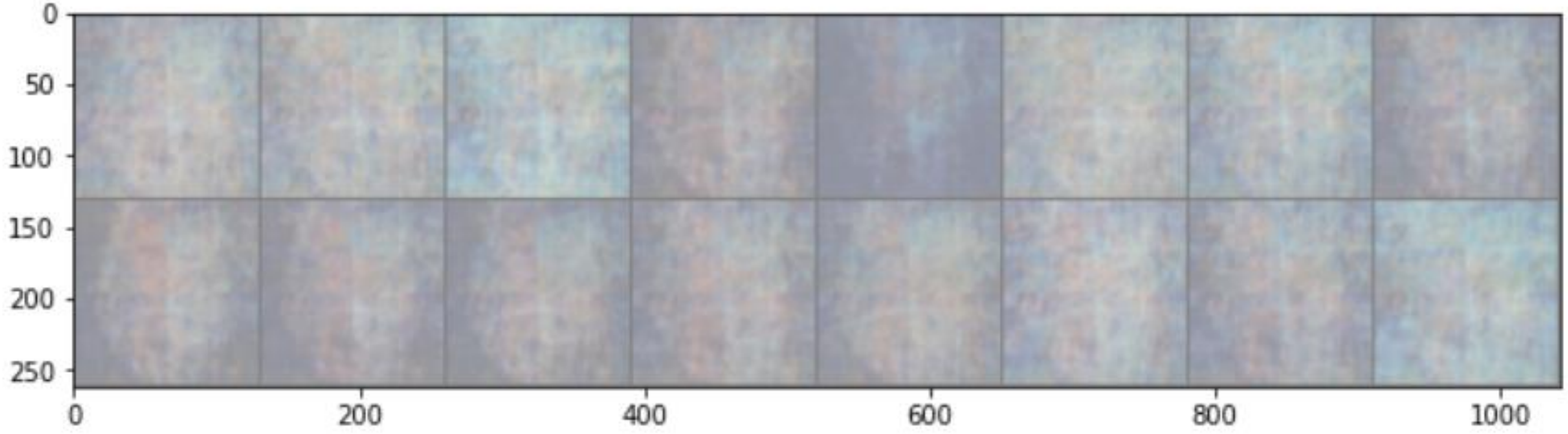
Test on training images – the NN is able to recover more from the input images



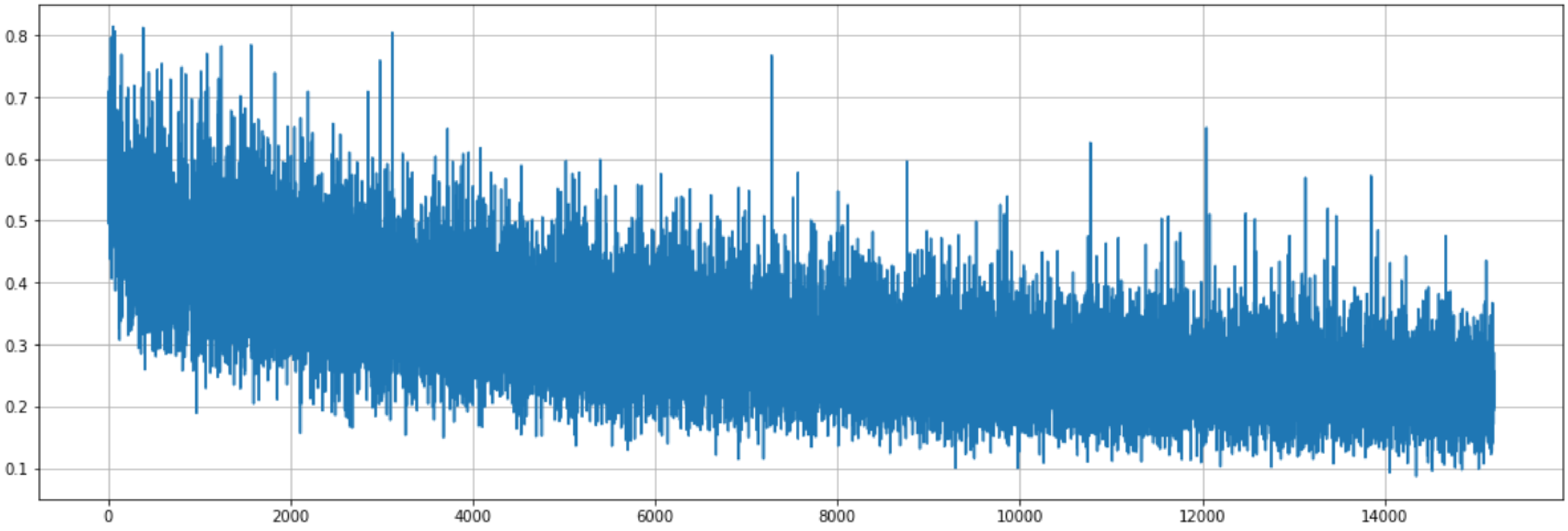
Train 200 epochs

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



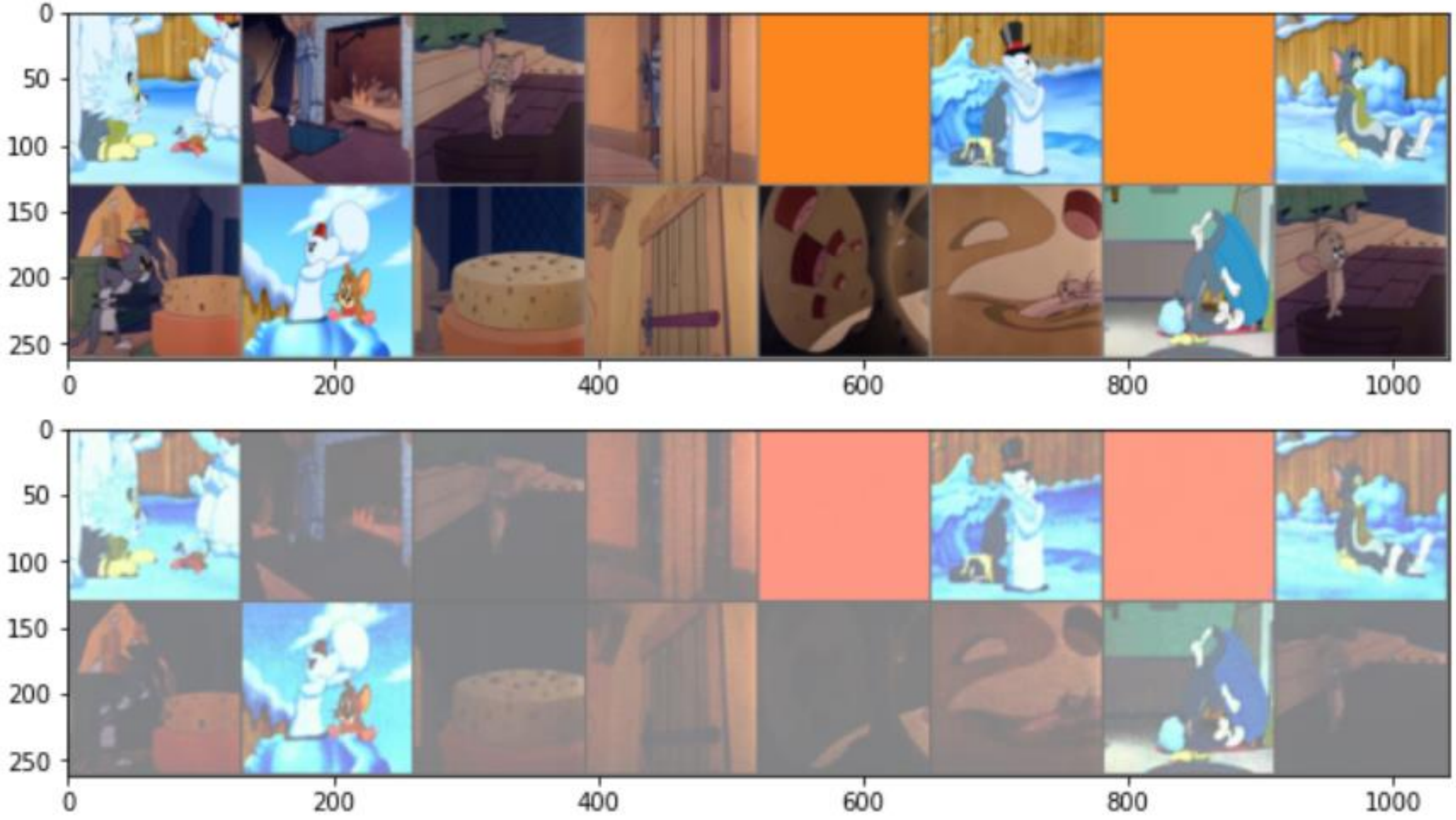


Train 800 epochs



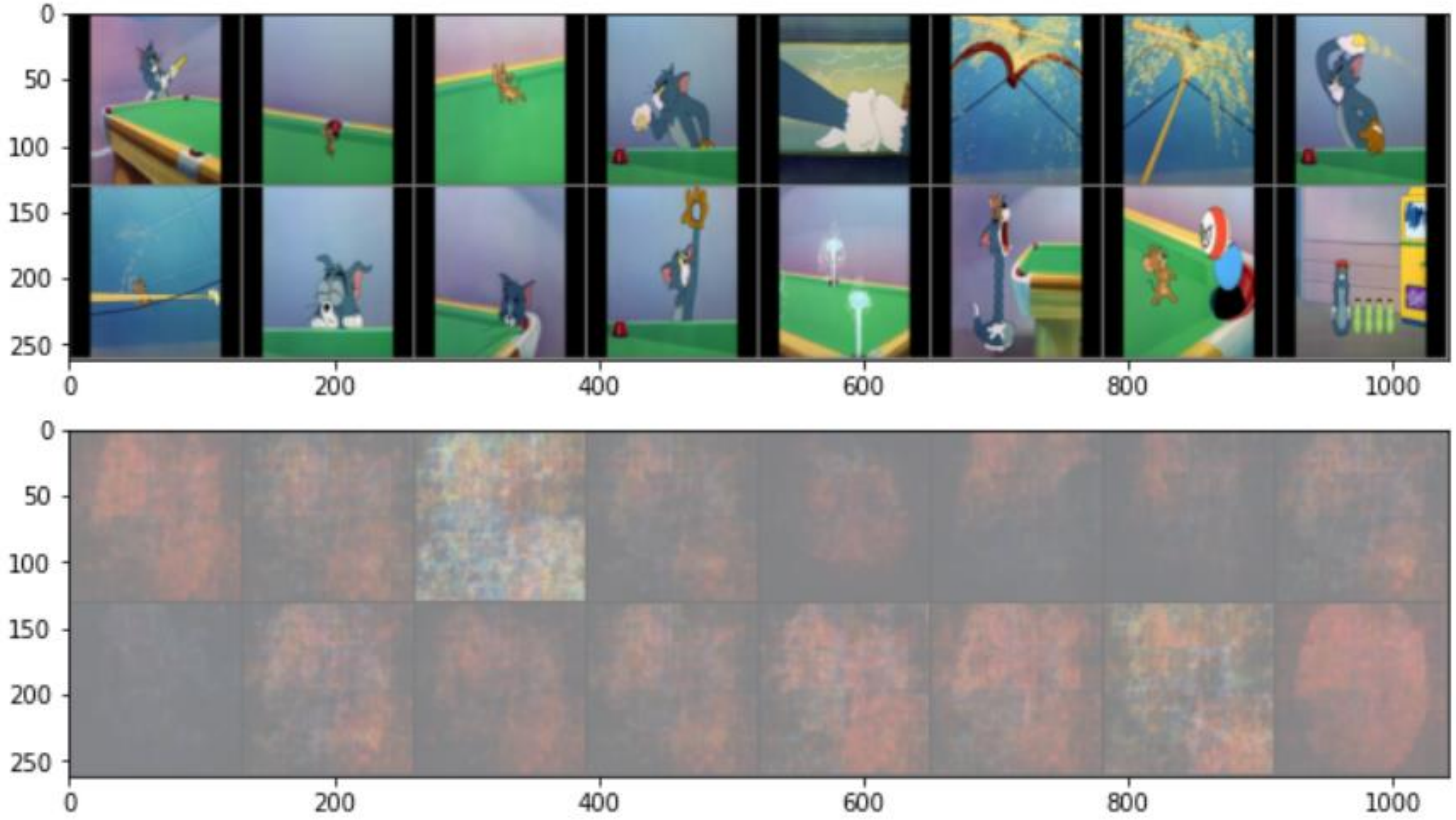
Train 800 epochs

Test on training images

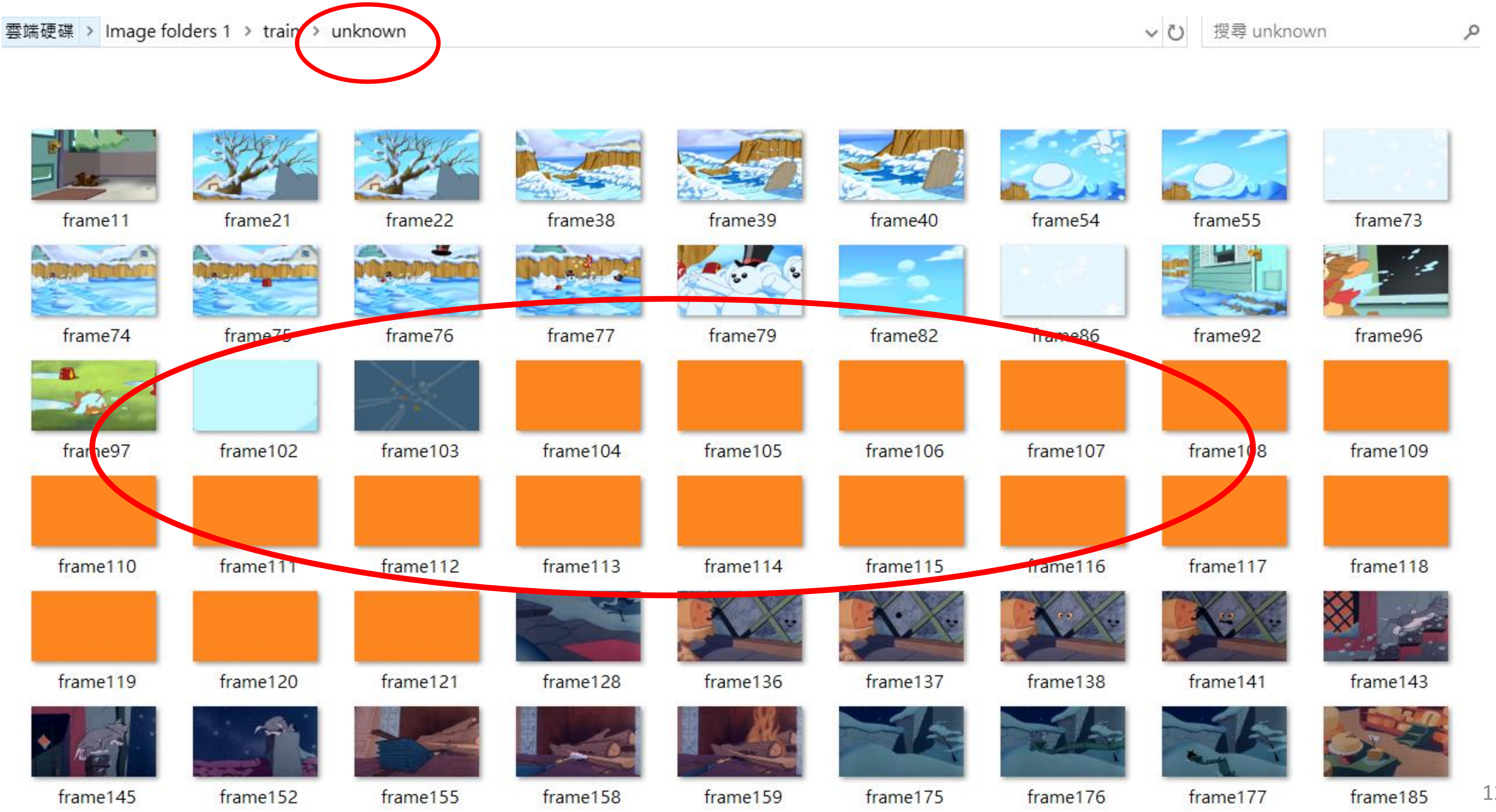


Train 800 epochs (same results when train 1200 epochs)

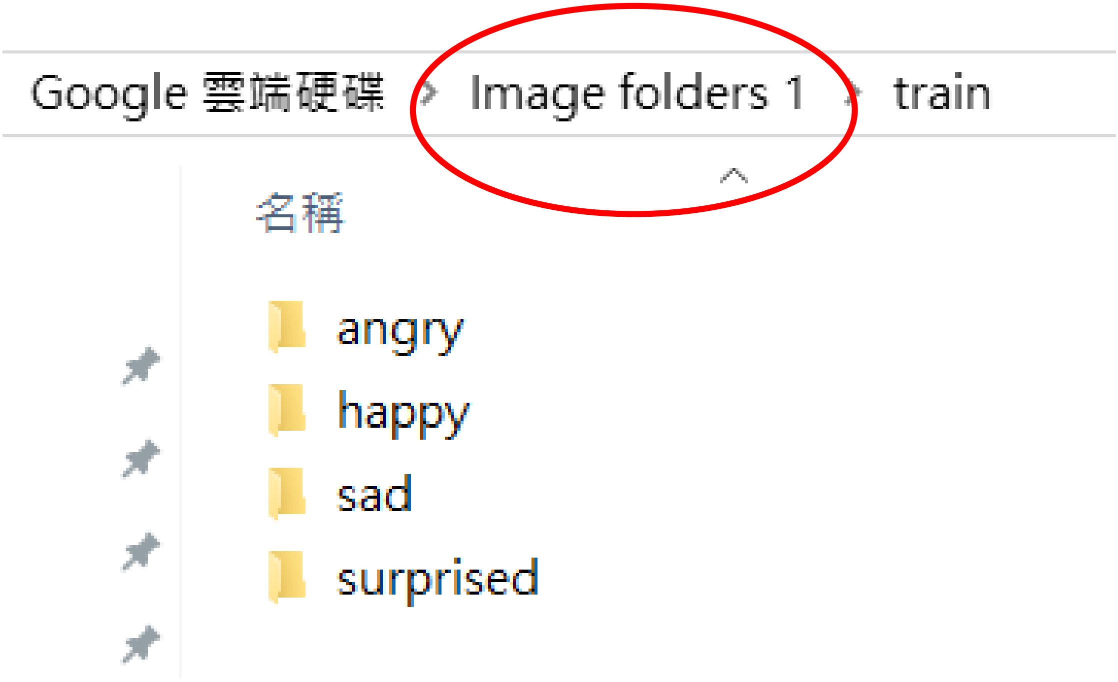
Test on un-seen images – fails to reconstruct the input images



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

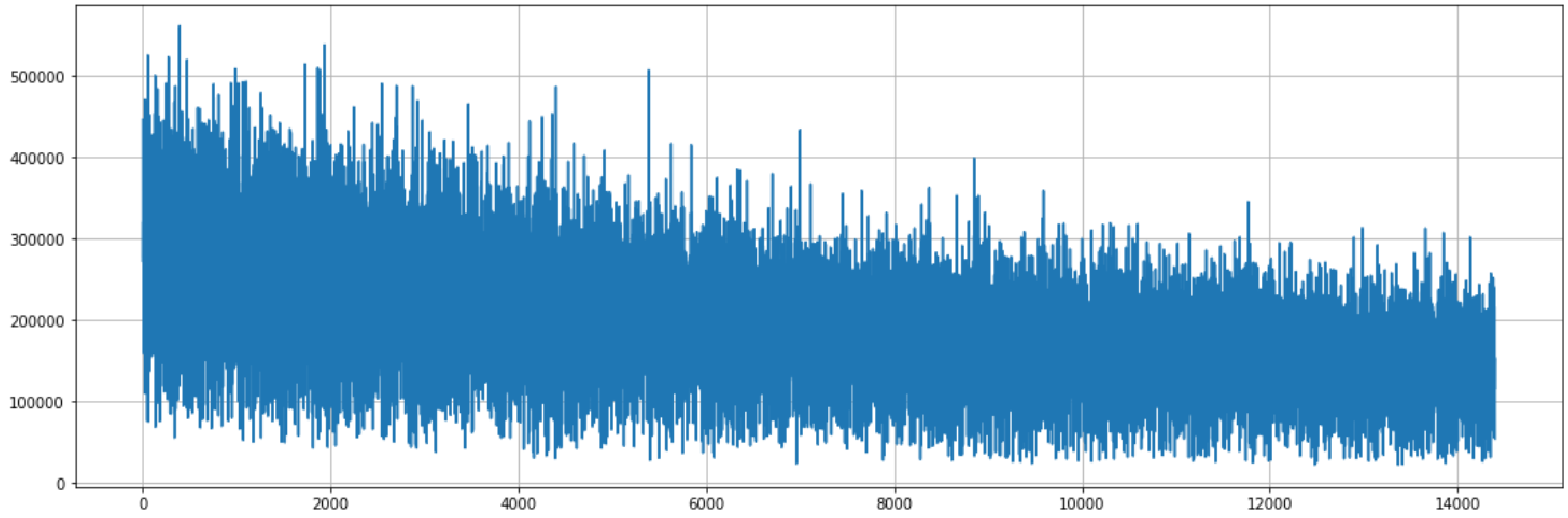


Create a new folder "Image folder 1", remove the "Unknown" sub-folder

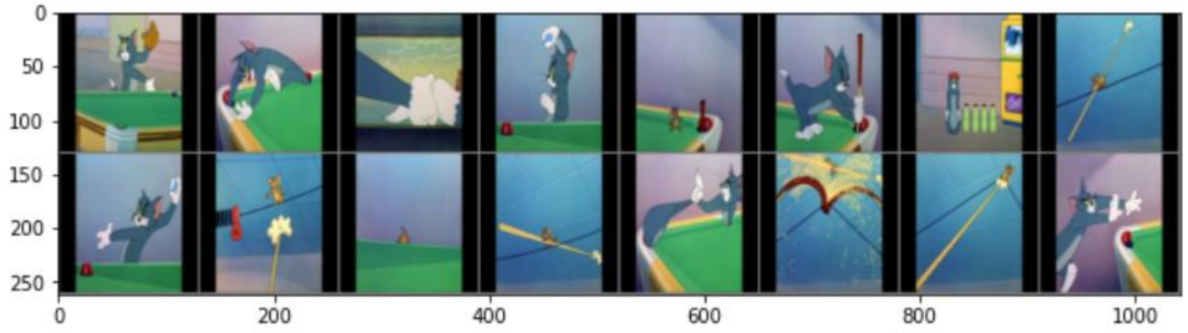


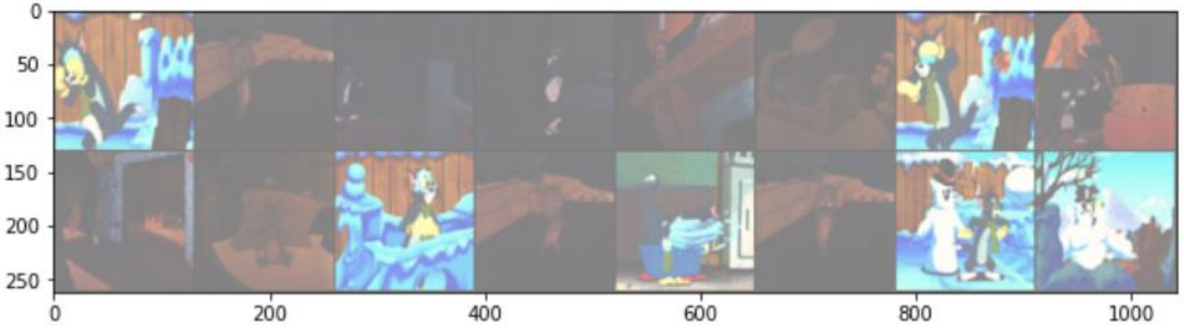
Test folder remains the same

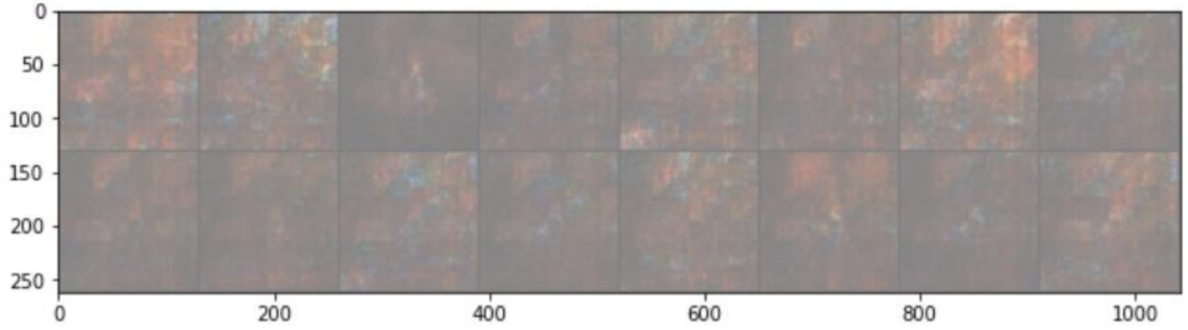
Train 1200 epochs after removing the "unknown" folder



Train 1200 epochs after removing the "unknown" folder

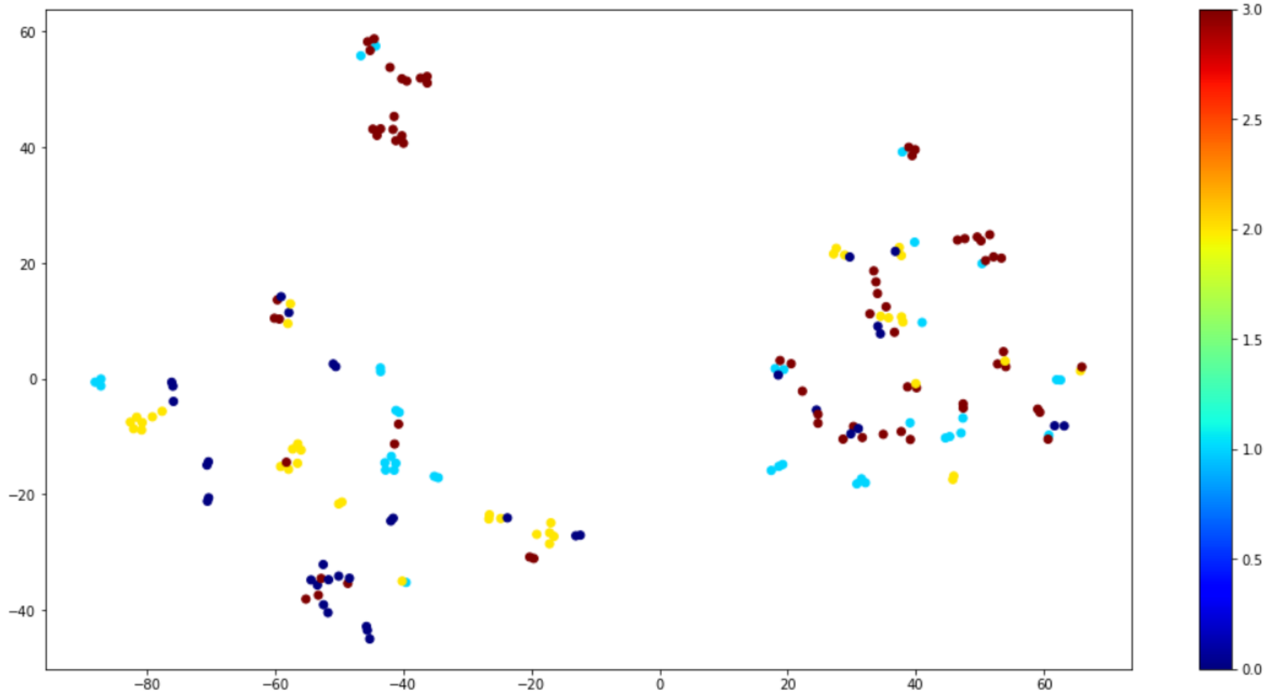






Train 1200 epochs after removing the "unknown" folder

perplexity = 5



perplexity = 10, 30, 50

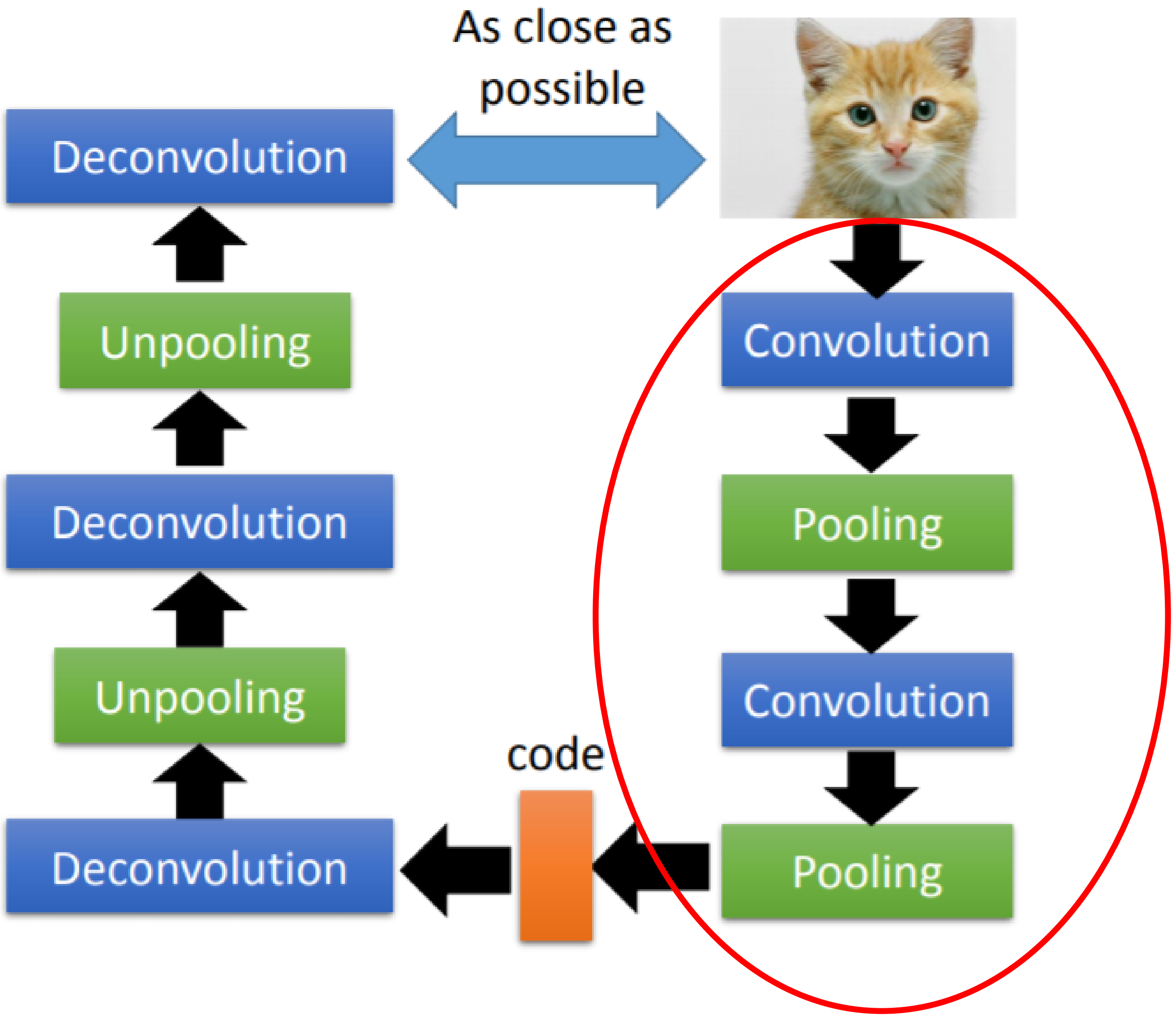
How about batch size? Increase or decrees ?

```
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)
```

Epoch=1200, batch size=32 or 16

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),
)
```

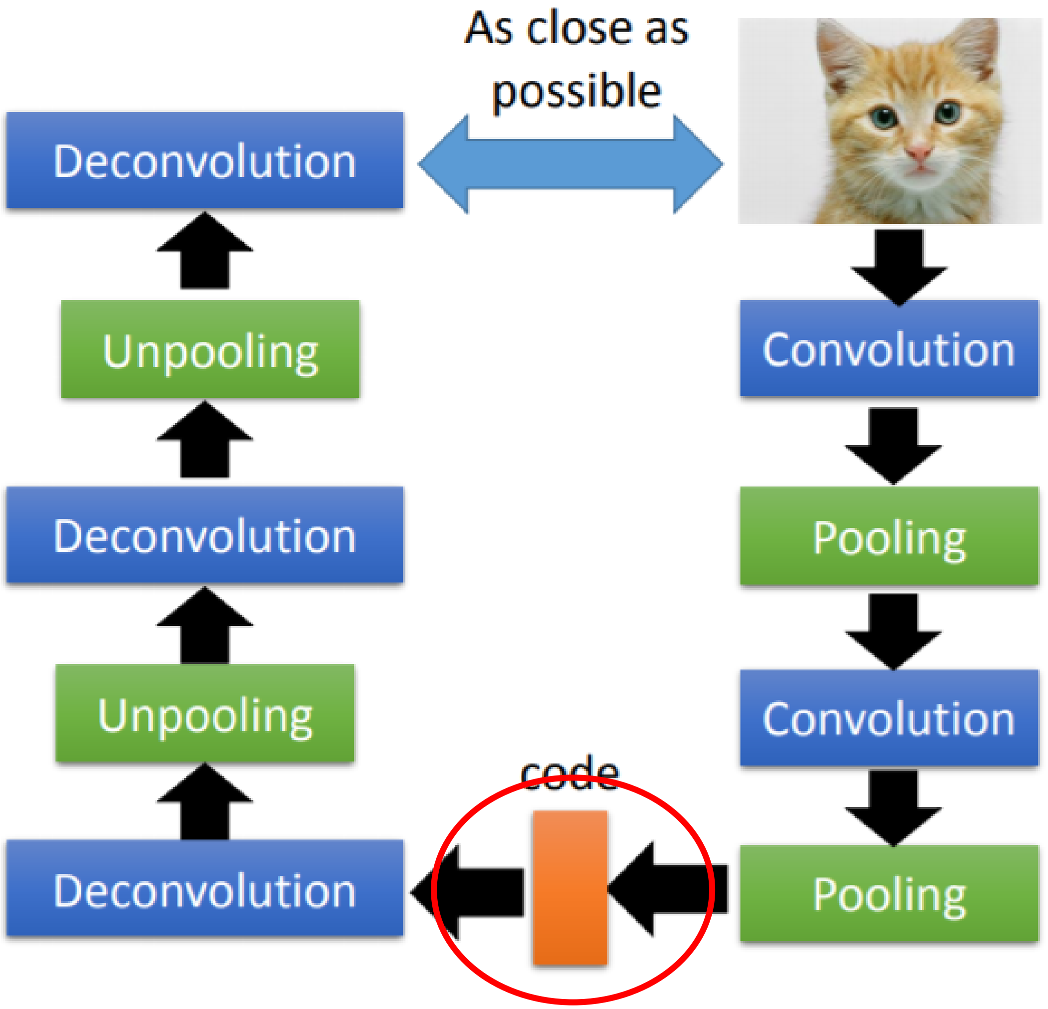
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

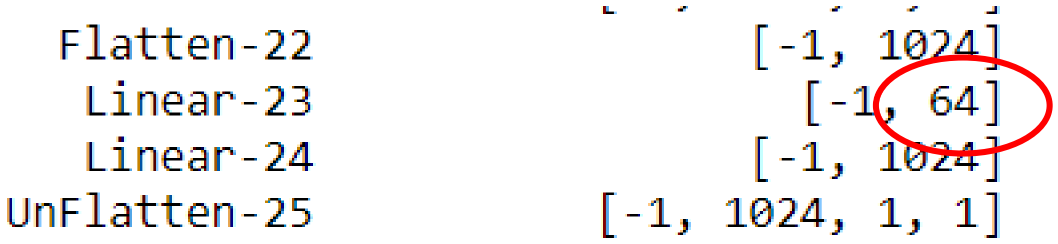
Practice: Draw the feature maps of encoder

- 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

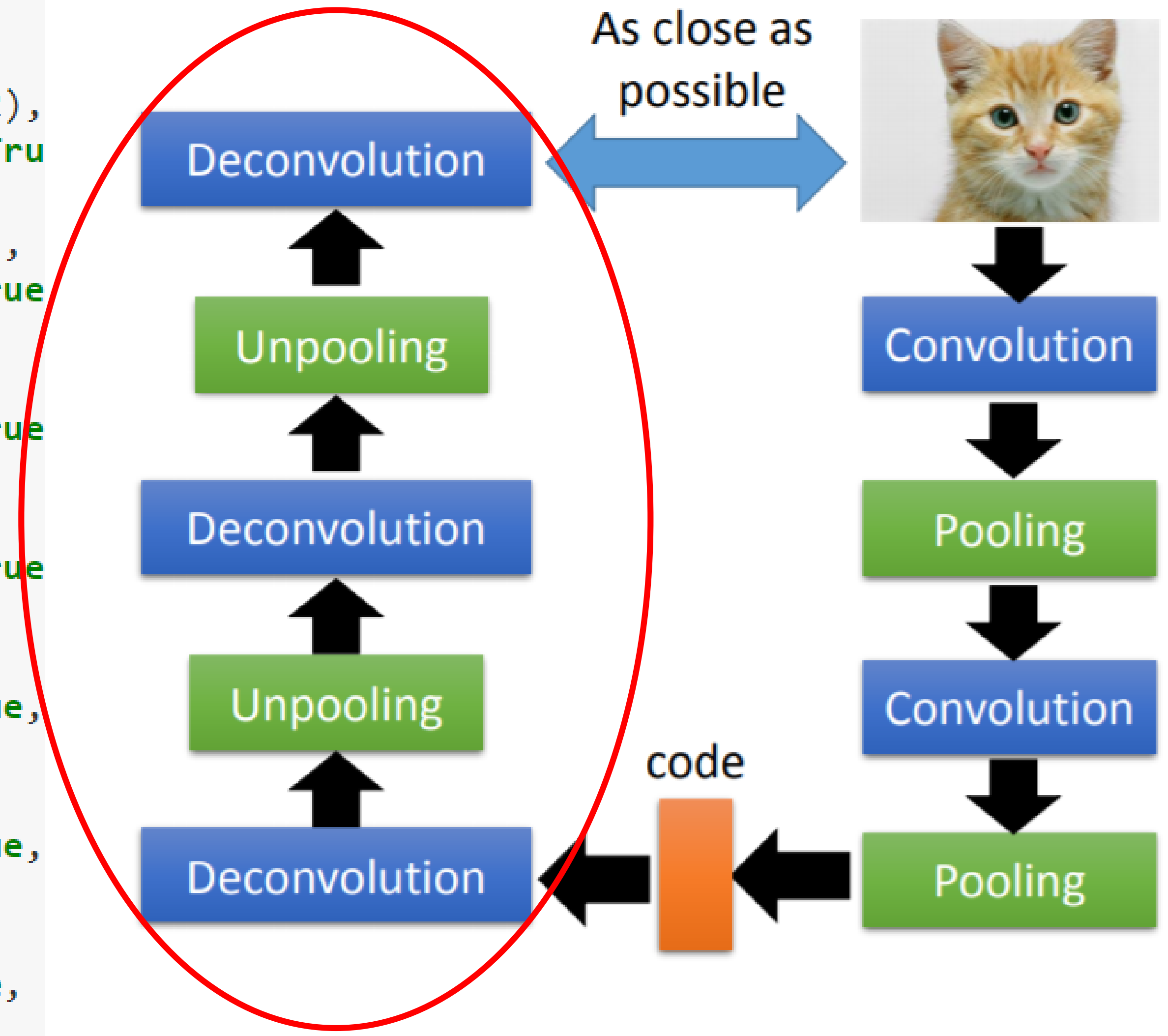




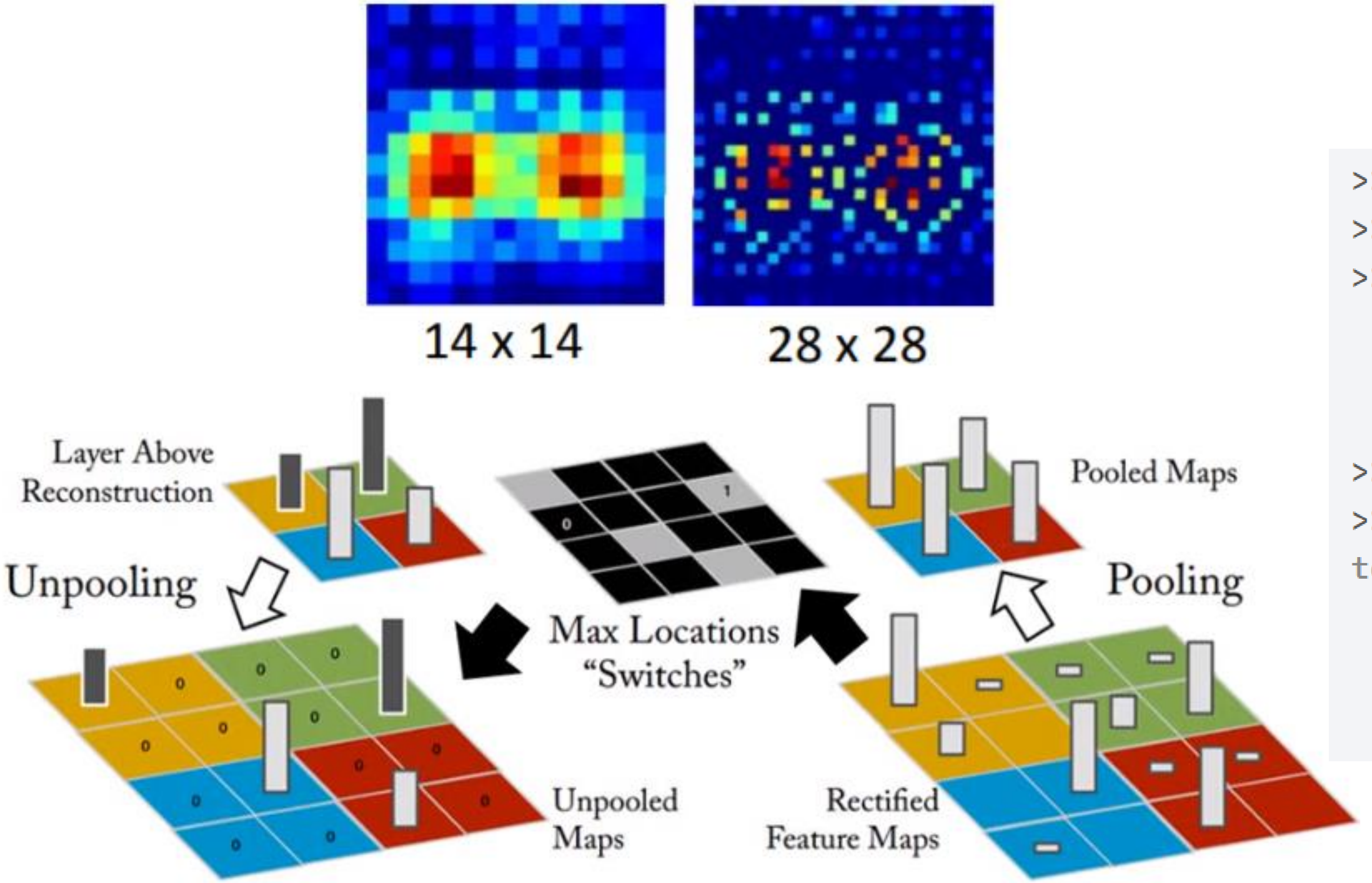
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

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(),
)
```



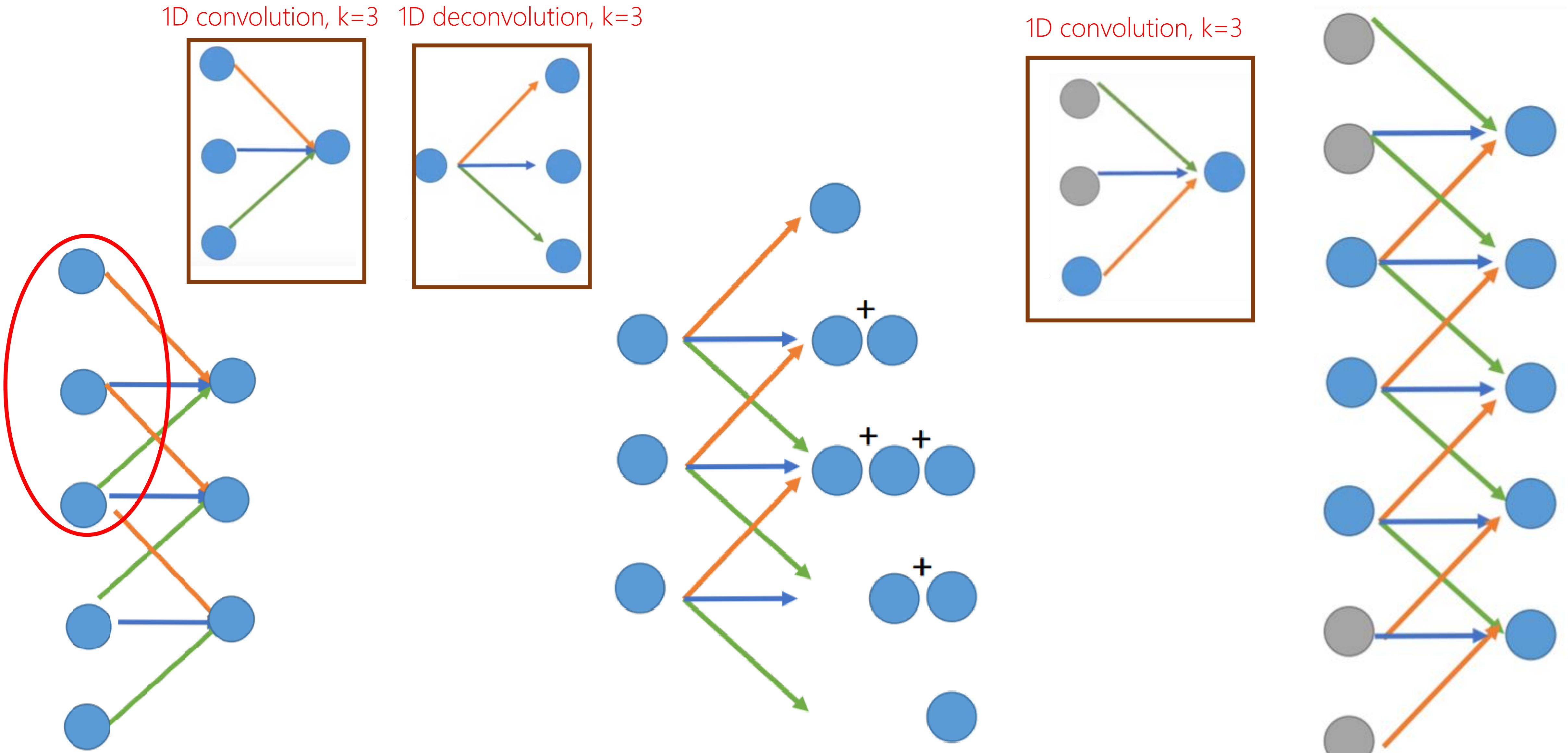
Unpooling




```
>>> 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

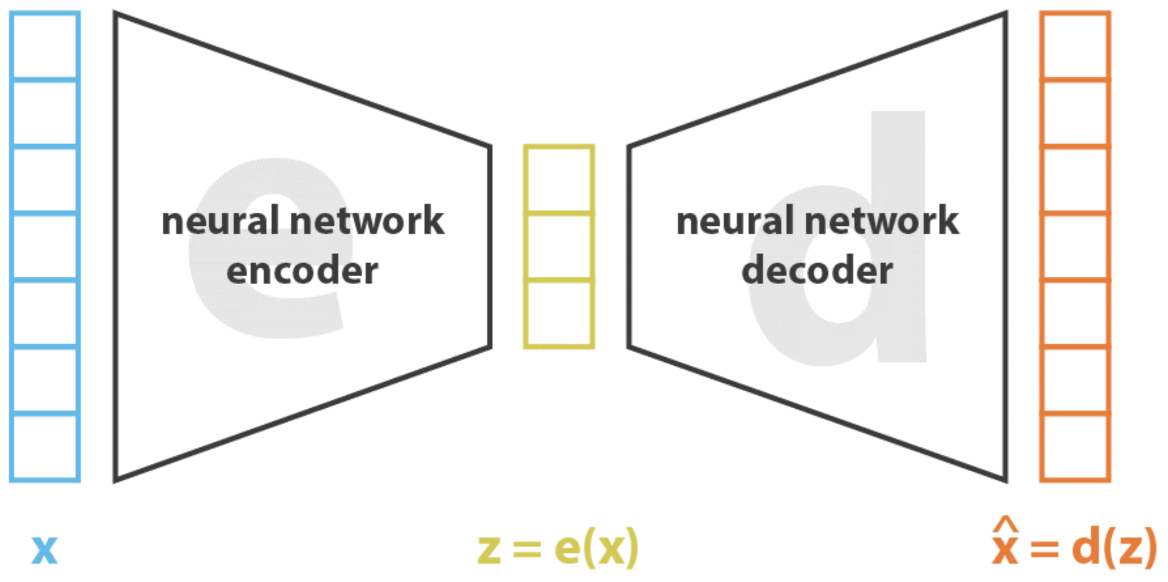
PYTORCH

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()
```

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
```

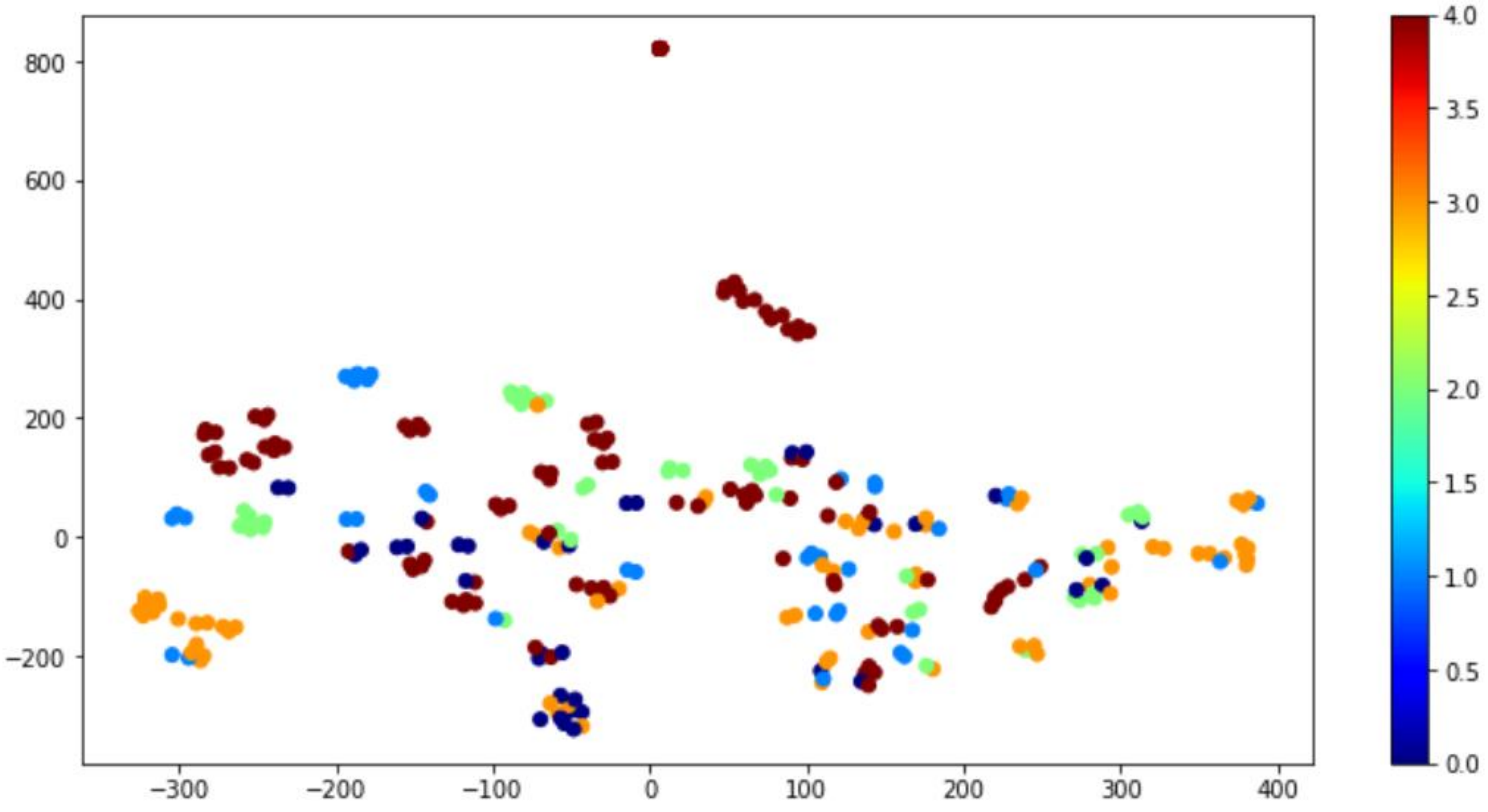
[39]:
```
x=tsne.fit_transform(arrayX)
print(x.shape)
```

```
(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

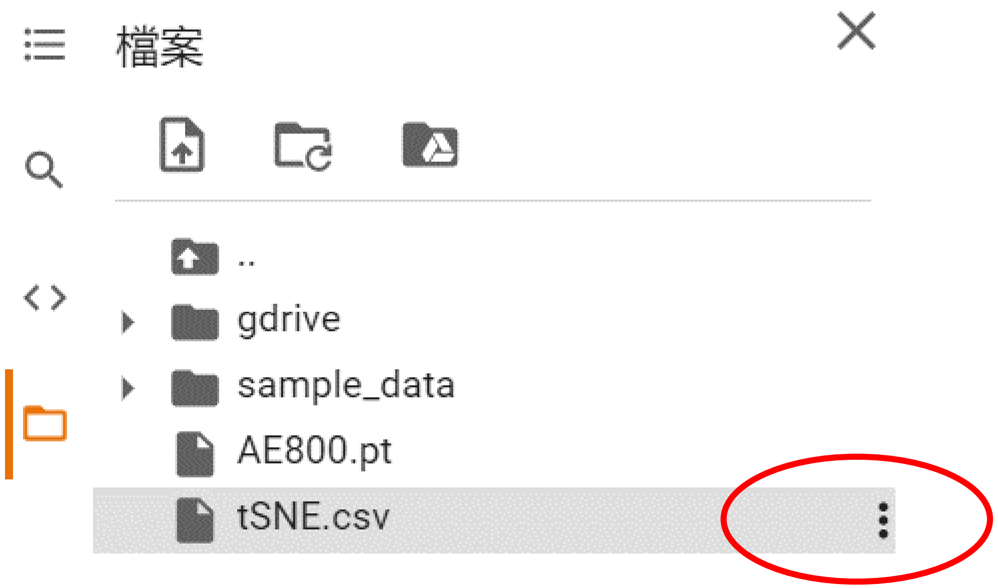


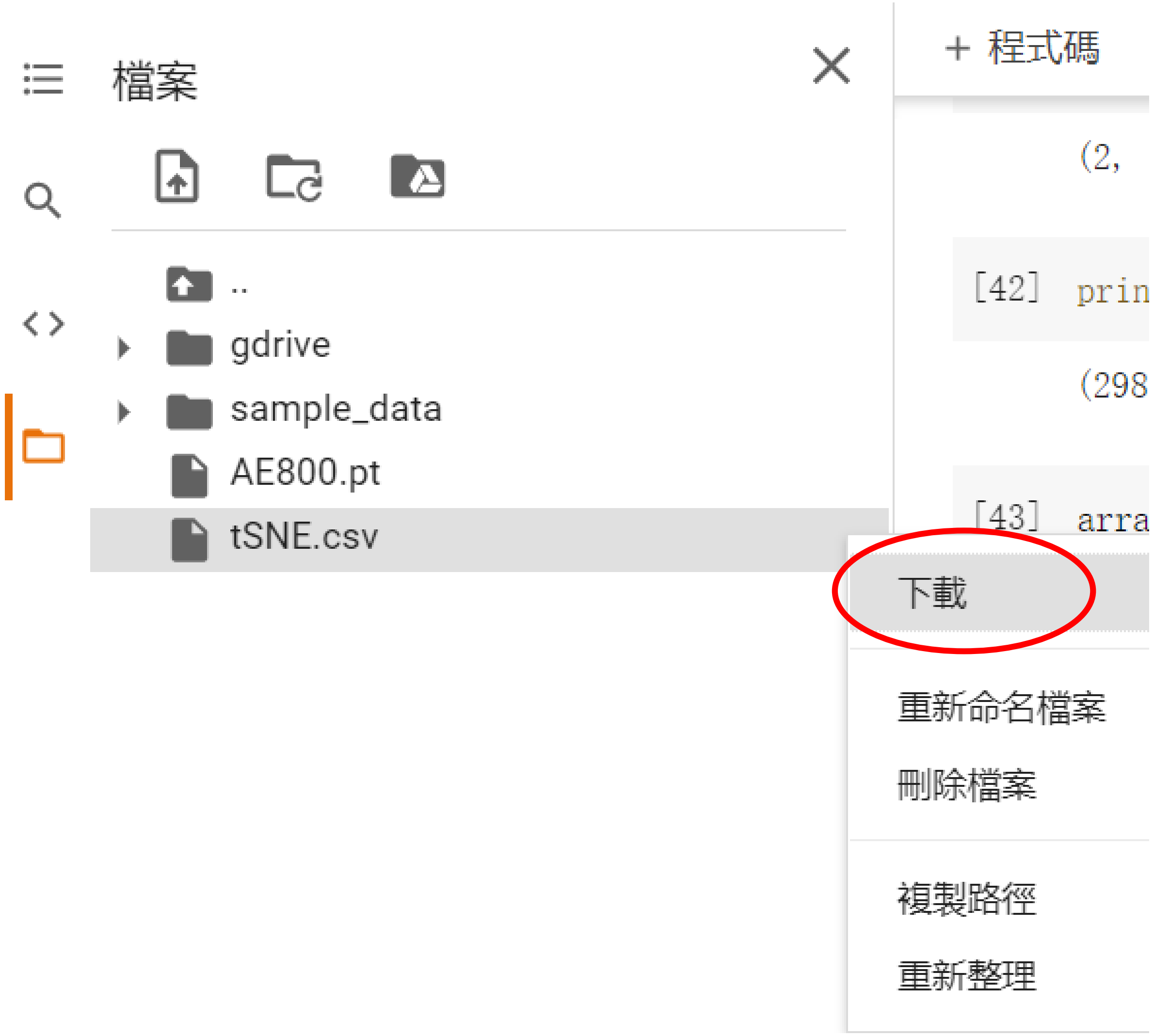
Save data to csv file

```
[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")
```

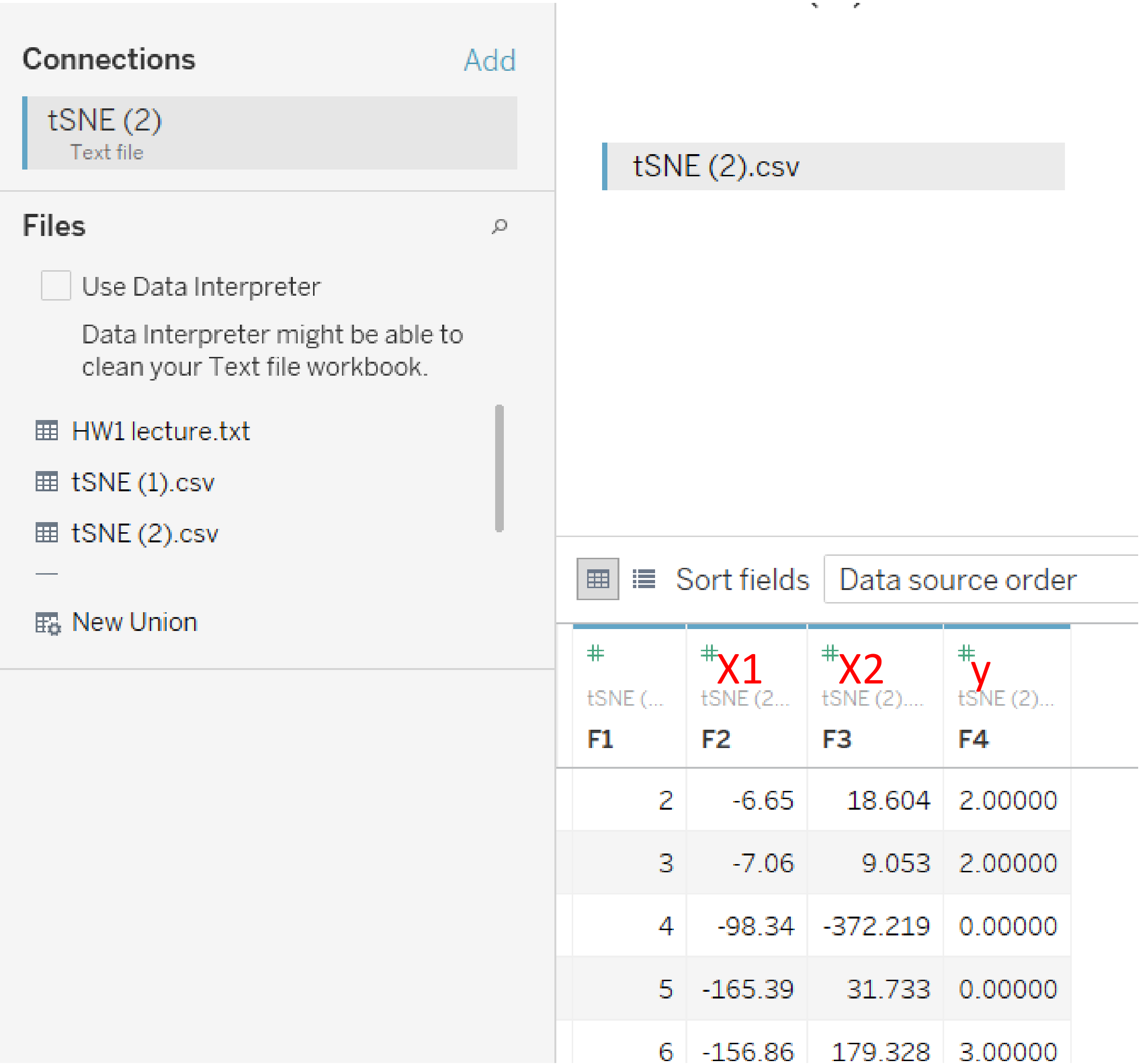
Save data to csv file

Download csv file



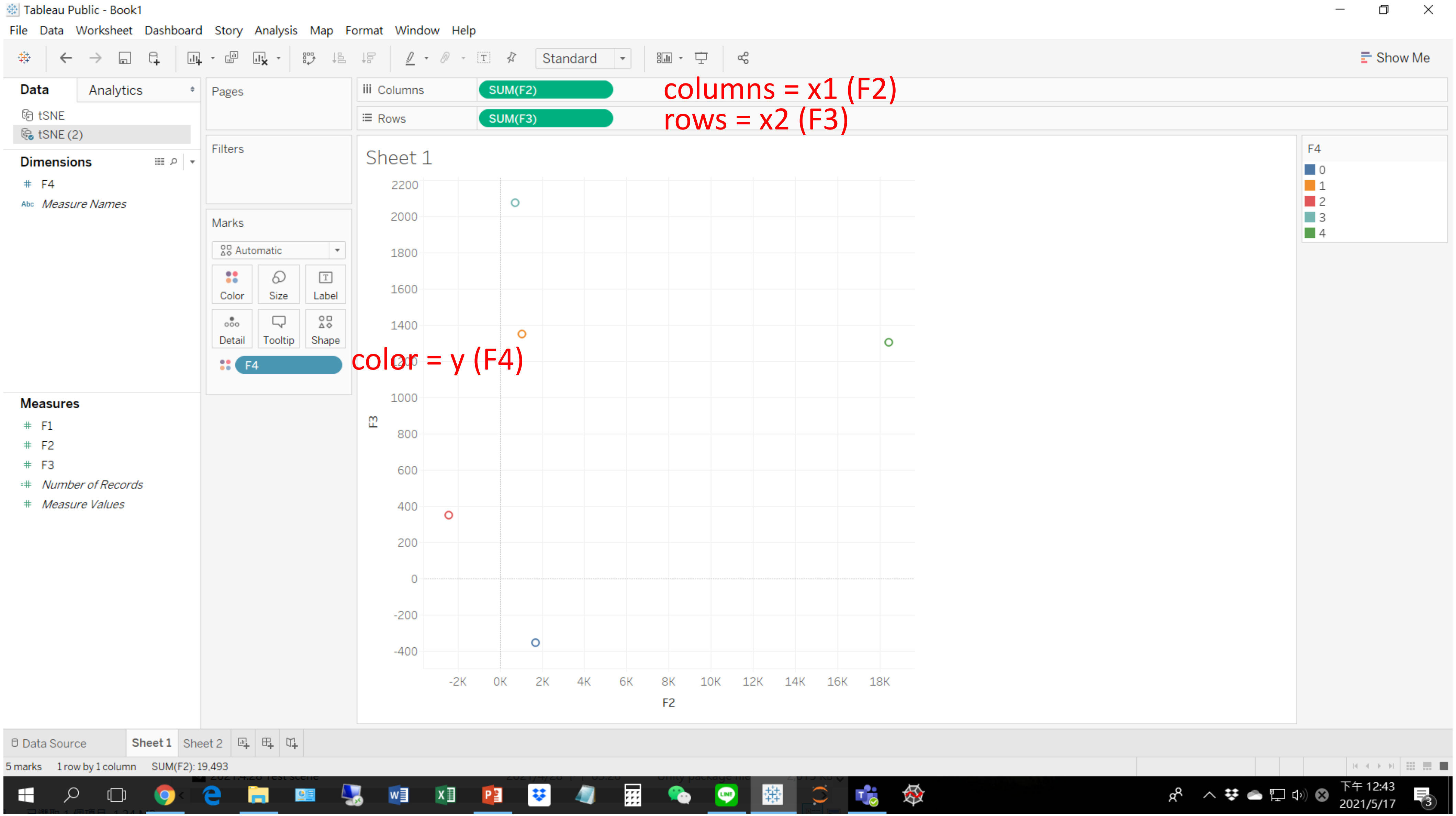


Visualize in Tableau public

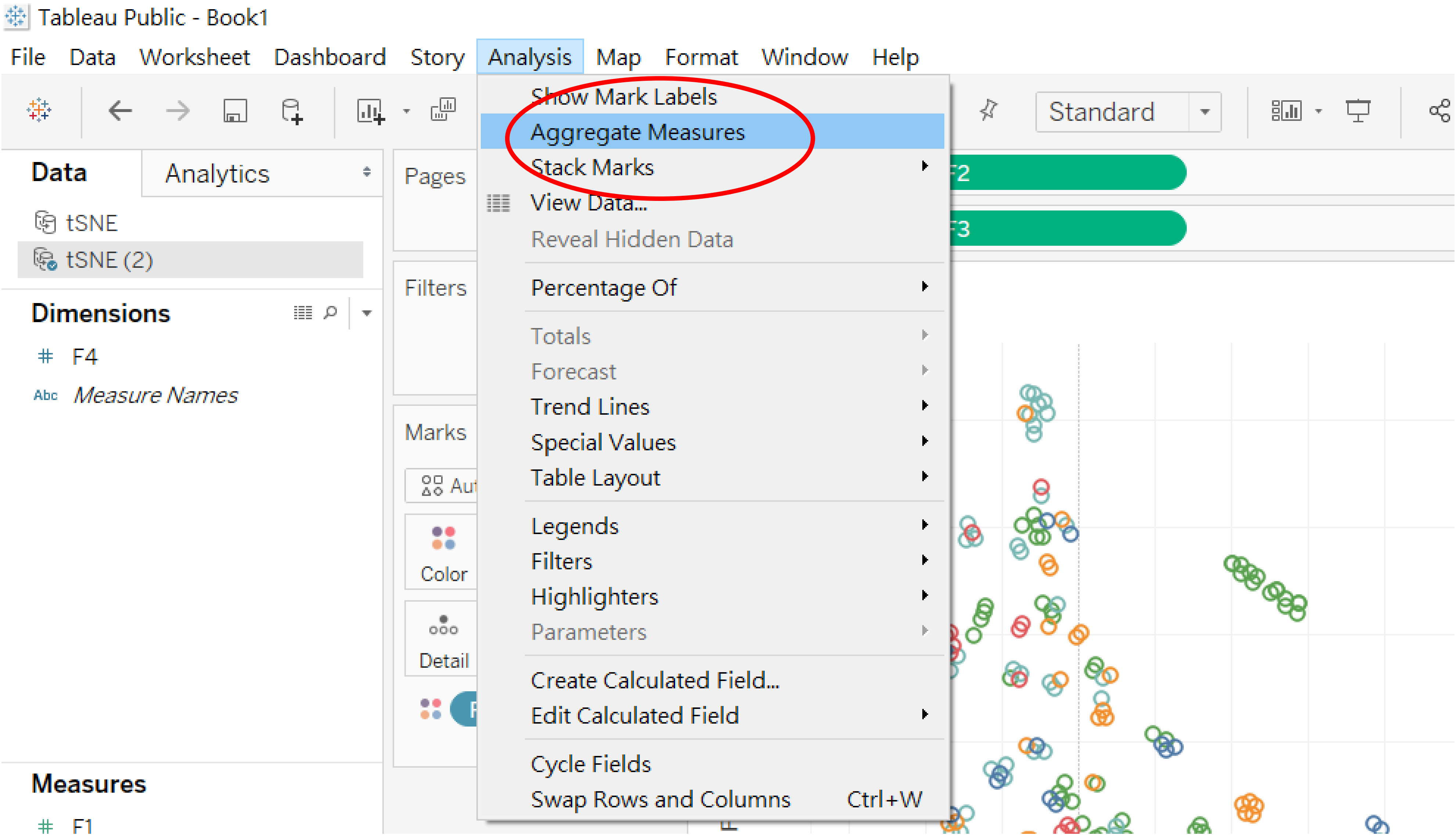


tSNE (... F1	tSNE (2... F2	tSNE (2).... F3	tSNE (2)... F4
2	-6.65	18.604	2.00000
3	-7.06	9.053	2.00000
4	-98.34	-372.219	0.00000
5	-165.39	31.733	0.00000
6	-156.86	179.328	3.00000

Visualize in Tableau public



Visualize in Tableau public



Visualize in Tableau public